ABSTRACT

JODI S. BAKST. Assessing Data Quality for Life Cycle Assessment. (Under the direction of Dr. Deborah Amaral)

Life cycle assessment (LCA) is an analytical decision support tool used to identify and evaluate opportunities to reduce environmental impacts associated with products, processes, packages, materials, activities. LCA has three primary components: development of a quantitative life cycle inventory (LCI), conduct of an impact assessment (IA), and evaluation and implementation of environmental improvements.

LCAs typically use a multitude of data sources and types to draw important conclusions about products and processes. Most LCAs released to date have included minimal data quality evaluations. This document uses the concepts of quality assurance/quality control (QA/QC), decision analysis, and the data reliability indicator system developed by Kollig, to develop a framework for the assessment of LCA data quality. The framework includes a quantitative scoring system to evaluate LCA parameters against certain data quality indicators, and a system of data quality worksheets and a data quality matrix to translate the information into a usable format.

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LIST OF ACRONYMS

CV	Coefficient of Variation
DQG	Data Quality Goal
DQI	Data Quality Indicator
DQO	Data Quality Objective
DQS	Data Quality Score
DRI	Data Reliability Indicator System
DU	Data Usability
GDQP	Good Data Quality Practices
IA	Impact Assessment
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
NUSAP	Numerical, Unit, Spread, Assessment, Pedigree Method
QA/QC	Quality Assurance/Quality Control
QAPJP	Quality Assurance Project Plan
SETAC	Society of Environmental Toxicology and Chemistry
TRI	Toxic Release Inventory

CHAPTER 1
INTRODUCTION

Life Cycle Assessment (LCA) is an analytical tool used to identify and evaluate opportunities to reduce environmental burdens and associated impacts of products, processes, packages, materials, or activities. Practitioners use this methodology to analyze the entire life cycle of industrial processes by gathering data on, and assessing the impacts from, raw materials extraction and processing; manufacturing, transportation, and distribution; use/reuse/maintenance; recycling and composting; and the final disposition of materials.

The LCA approach has three components:

- developing a quantitative life cycle inventory (LCI) of energy, resource use, and environmental emissions to air, water, and land;
- conducting an impact analysis (IA) of the effects of these emissions on the environment using the LCI data; and
- evaluating and implementing opportunities to effect environmental improvements.

LCA practitioners and researchers, however, consider goal definition and scoping to be the fourth component of an LCA. These steps, which are taken prior to - or at the outset of - an LCA involve linking the goals of the analysis with the extent or scope of the overall study (EPA, 1992b). Goal definition entails identifying and defining the purpose and objectives of the LCA, setting the boundaries for the analysis, and identifying the study's overall data needs. LCA goals are revisited repeatedly to ensure and maintain consistent definition throughout the conduct of the study. Scoping is used to define the extent of coverage for an analysis. This includes identifying the process(es) or product(s) to be evaluated, the impacts or system parameters of concern, users of the study, and whether the analysis will be publicly available (i.e., internal versus external), and absolute or comparative. In short, goal definition and scoping is viewed as a key phase in the LCA process because practitioners use it to define the overall purpose and objectives of an LCA, based on known time and resource constraints.

To date, most practitioners have compiled inventories and drawn conclusions (e.g., the least or most environmental impact) based on simple data aggregation techniques. Few practitioners have conducted actual impact analyses based on inventory data. In the future, however, as LCA tools and techniques are refined practitioners are expected to conduct more impact analyses and improvement analyses . This document follows current convention and uses the term "LCA" to refer to both the life cycle inventory and life cycle impact analysis phases of an LCA.

A variety of organizations use the LCA methodology to serve a number of different purposes. Companies use LCA results internally to support management decisions on production processes, product design, and product packaging. Companies also use LCA results externally to advertise a single product or advocate one product over another. Government agencies use LCA results to support both policy and regulatory decisions. Consumer and environmental groups also utilize LCA results to compare the environmental "friendliness" of competing products.

LCAs require the acquisition and synthesis of significant amounts of data. Given the data-intensive nature of this methodology, and the important decisions that are made based on LCA results, data quality is a critical concern. LCA practitioners usually undertake some level of data quality evaluation. However, the rigor with which that evaluation is applied, and the extent to which LCA reports discuss data quality varies significantly. Important problems can arise if LCA results are based on data of poor or inadequate quality. For example, if internal analyses are conducted, misleading results could cause costly process or product decisions. Conclusions based on external analyses where poor data were used could result in misleading the public in the belief that one product is superior to another. Due to concerns such as these, there is a growing consensus among LCA practitioners that data quality evaluations need to be incorporated into LCAs more formally and the results discussed more fully in future LCAs (ADL, 1993)

1.1 THE CURRENT STATE OF DATA QUALITY EVALUATION IN LCA

Data quality evaluations typically are found in studies that contain primary data (i.e., facility-specific, measured, monitored, or estimated data). When primary data are unavailable, however, analytical tools such as LCA often rely on secondary data sources (i.e., data collected for a different purpose than the LCA being conducted). Currently, there is a lack of formal guidelines to assess the quality of data other than those generated pursuant to statistical protocols. Practitioners recognize that because the decisions that come out of LCAs are used in influential ways, there is a need to develop appropriate data quality assessment procedures. On a general level, practitioners have suggested evaluating LCA data quality against traditional data quality indicators, such as accuracy, representativeness, and completeness, and employing sensitivity analysis to determine the most sensitive LCA parameters (SETAC, 1991; EPA, 1992b). This document discusses the applicability of these and other approaches to an evaluation of LCA data quality.

1.2 WHAT IS DATA QUALITY?

What does it actually mean to have good data quality? From a philosophical standpoint, there are two components of data quality. Some would argue that the sole basis for determining if data are of good quality is whether they represent, or correspond to reality. Others would argue, however, that good data quality depends not only on their correspondence, but their intended use. In other words, for data quality to be considered "good," data must both reflect what they are supposed to, and be applicable to the particular situation under evaluation. The following pages provide a framework for assessing the quality of data used in LCAs. Under this approach, data quality evaluations are based both on what the data represent and how the data are applied.

1.3 SCOPE OF DOCUMENT

This document presents a framework for evaluating LCA data quality and translating this information into a usable format that includes a quantitative data quality scoring system, data quality worksheets, and an LCA data quality matrix. The document discusses where and how data quality should be considered when conducting an LCA, what type of data quality goals should be set, and what data quality indicators are appropriate based on the type of data used in LCAs. The document also defines good data quality practices (GDQPs) for LCAs. This process includes incorporating the results of data quality evaluations into LCA reports to both increase the transparency of LCAs and enhance their overall credibility.

Users of this document may include

- practitioners who are conducting LCAs,
- analysts who are working to develop and improve LCA methodologies,
- analysts who need to assess the quality of data used in existing LCAs, and
- decision makers who use LCA results.

The framework presented below provides a systematic approach for assessing LCA data quality. The quantitative scoring system, although subjective in nature, adds methodological rigor to the data quality evaluation process. Even though the scoring system may be time consuming in the early stages of its use, it will provide LCA practitioners with increased confidence to accept or reject LCA data sources, and ultimately in LCA results.

Although practitioners should consider and incorporate data quality evaluations into all LCAs, the framework is most applicable to external analyses. Unlike internal LCAs, results of external analyses are made publicly available. Practitioners use external LCA results to educate the public about products and processes, or to advocate a particular public policy issue. Given the public nature of the information, identifying the accuracy of LCA results is an important concern. If practitioners conducting external analyses evaluate data quality, and summarize the results according to the framework set forth in this document, users or recipients of the analyses will have increased confidence in LCA results.

1.4 OVERVIEW OF DOCUMENT

Chapter 2 reviews the data sources and data types typically used when conducting an LCA and discusses potential problems with data quality. Chapter 3 provides a flow chart of the steps associated with building the inventory component of an LCA, during which essentially all of the data are collected, and discusses the implications for data quality at each step.

Chapter 4 explains the concepts of data quality goals (DQGs) and data quality indicators (DQIs) and describes specific DQIs applicable to evaluating LCA data quality. Chapter 5 outlines a quantitative data quality scoring system based on DQGs and DQIs and provides report cards and a data quality matrix as a means to translate the information into a usable form. Chapter 6 reviews sensitivity and uncertainty analysis methodologies and their potential applicability to LCA. Chapter 7 discusses methods for handling missing data and data deficiencies found in LCA data sources. Chapter 8 summarizes the information presented in this document into a set of GDQPs for LCAs.

Appendices A through D provide information on alternative data quality assessment methodologies and discuss their applicability to assessing LCA data quality. Appendix A reviews traditional, statistically based procedures, referred to as the "quality assurance/quality control" (QA/QC) method. Appendices B through D present three qualitative approaches to data quality assessment: the Numerical, Unit, Spread, Assessment, Pedigree (NUSAP) method developed by Funtowicz and Ravetz (1990); the Data Reliability Indicator (DRI) system developed by Kollig (1987); and the Data Usability (DU) criteria developed by EPA (1990).

1.5 ISSUES OUTSIDE THE SCOPE OF THE LCA DATA QUALITY FRAMEWORK

In addition to data quality concerns, three issues are important to the problem of increasing the transparency of LCA results: the development of an LCA peer review process, a code of good LCA practice, and a framework for conducting life cycle impact assessments. It is beyond the scope of this framework to define or discuss any of these issues in detail. Rather, they are addressed only in their relationship to LCA data quality concerns.

1.5.1 Peer Review

The Society for Environmental Toxicology and Chemistry's (SETAC) document, "Technical Framework for Life-Cycle Assessment," indicated that peer review is a necessary and important step to ensure the technical and scientific credibility of LCAs. In response, SETAC identified an LCA Advisory Group that developed an Interim Peer Review Framework (SETAC, 1992b). The framework recommends, among other things, that a peer review panel be established at the beginning of any LCA, and that LCA practitioners and sponsoring organizations have the panel review:

- the study purpose, boundaries, and data categories,
- the stand-alone data, and
- the draft final report.

In general, the Interim Peer Review Framework provides LCA practitioners and sponsoring organizations with a recommended set of guidelines to begin incorporating peer review into LCAs. As discussed below, the LCA data quality framework recommends that peer or expert review be incorporated into the data quality assessment process. The data quality framework, however, does not define an appropriate peer review process for LCAs. Rather, LCA peer review procedures will continue to be identified and developed by SETAC.

1.5.2 Code of Good LCA Practice

There is growing interest in the need for a code of good LCA practice. The inconsistency and uncertainty in LCA results has resulted in the recognition of the need for a standardized LCA methodology (Denison, 1992). The LCA data quality framework sets forth good operating principles for the evaluation and reporting of LCA data quality. The framework does not, however, outline a code of good practices for the entire LCA process. The development of such principles has been, and will continue to be, undertaken by SETAC. In fact, this topic was the subject of a recent SETAC World Congress workshop in Lisbon, Portugal (March 28-31, 1993).

1.5.3 Life Cycle Impact Assessment

Data quality concerns also exist when conducting the second phase of an LCA, a life cycle impact assessment. This document discusses different data quality concerns that may arise when gathering an inventory only or when conducting an impact assessment. This document, however, does not discuss the framework for conducting an impact assessment, or the broader issues related to this phase of an LCA. Rather, these issues are addressed in EPAs draft final report entitled, "Life Cycle Impact Assessment Part I: Issues" (EPA, 1993).

CHAPTER 2
DATA QUALITY ISSUES IN LIFE CYCLE ASSESSMENT

Analysts use many different types and sources of data in LCAs. Some analysts use primary data (facility-specific, measured, monitored, or estimated data), while other analysts use secondary data (data collected for a different purpose than the LCA being conducted). Primary and secondary data used in LCAs typically are of the following types, measured, modeled, and nonmeasured. Understanding the potential problems that can arise with different types and forms of data provides an analyst with a basis for evaluating data quality. This chapter defines data quality in the context of an LCA, reviews the data sources and data types commonly used by LCA practitioners, and discusses data quality problems that can occur with various types and forms of LCA data.

2.1 DEFINITION OF "DATA QUALITY"

The term data quality can take on a variety of meanings. For purposes of these guidelines, data quality is defined as the degree of confidence an analyst has in a data source or data value based on an evaluation of data quality goals (DQGs), data quality indicators (DQIs), and the role of the data in an overall LCA. (See chapter 3 for a detailed discussion of DQGs and DQIs.)

> Data quality is the degree of confidence an analyst has in a data source or a data value based on an evaluation of data quality goals (DQGs), data quality indicators (DQIs), and the role of data in an overall LCA.

The quality of LCA data sources is influenced by the primary or secondary nature of the data, the type of data employed (e.g., measured, modeled, or nonmeasured),.and the level of data aggregation (e.g., individual plant or industry average data). For example, secondary data sources are perceived as being less specific, and thus of lesser quality, than actual measured or monitored plant-specific data. Similarly, aggregated data may provide little indication of the variability in a parameter of interest, such as facility-specific air emissions. Nonaggregated data, on the other hand, can be used to calculate statistical measures such as the mean, standard deviation, and skewness to provide an indication of the central tendency and total variability in the data.

The remainder of this chapter defines data sources and data types typically used in LCAs and discusses the data quality problems that can arise with different types and forms of LCA data.

2.2 DATA SOURCES AND DATA TYPES USED IN LCAs

Data used in LCAs come from a wide range of sources and are of various types. In discussing LCA data quality it is important to develop consistent definitions of these terms. LCA data sources fall into several general categories (e.g., industry data, government documents or databases, and the open literature). A data type is defined as the data resulting from different data generation methods. Examples of different types of LCA data include measured data (statistically based or nonstatistically based), modeled data, and nonmeasured data (educated guesses or estimates).

> Data source includes a number of categories including industry reports; government documents, reports, and databases; journals; and reference books, etc.
>
> Data type is defined as the data that result from different data generation methods (e.g., measured, modeled, or nonmeasured data).
>
> Example: A data source could be the *Census of Manufacturers* and the data type could be measured data for SIC 2911.

2.2.1 Data Sources

Data sources have been defined fairly consistently throughout the LCA literature. Although different documents have specified varying levels of detail with respect to data sources, authors agree on the definition of a data source within the context of an LCA. Generally, LCA data sources include the following major categories (SETAC, 1991; EPA, 1992; EPA, 1991a; and EPA 1991b):

- industry data, reports, databases, or consultants,
- laboratory test data,
- government documents, reports, databases, or clearinghouses,
- other publicly available databases, or clearinghouses,
- journals, papers, books, and patents in the open literature,

- reference books (e.g., the Encyclopedia of Chemical Technology),
- trade associations,
- related LCIs, and
- product/process specifications.

Certain LCA documents provide examples of data sources within two or more of these categories. EPA's LCA Guidelines and Principles document indicates that sources of government documents include the U.S. Department of Commerce *Census of Manufacturers*; the U.S. Bureau of Mines *Census of Mineral Industries*; the U.S. Department of Energy *Monthly Energy Review*; and EPA's TRI database (EPA, 1992b). SETAC's 1991 LCA report also refers to data sources in general categorical terms and provides specific examples of information sources within the different source categories. Table 2-1 provides additional examples of LCA data sources.

2.2.2 Data Types

No prior attempt has been made to categorize, or define, different data types. Rather, various terms, such as industry-average or annual data, have been used as examples of different data types. Within the LCA context, the term "data type" has been used to refer to:

- the level of data aggregation (e.g., industry average, annual, individual plant, etc.) (SETAC, 1990; and EPA, 1992);
- the LCA input/output data category (e.g., energy, water, and raw material inputs and waste stream outputs) (EPA, 1991a; EPA, 1991b), and.
- data resulting from different data generation methods (e.g., measured, modeled, or nonmeasured data).

Multiple uses of the term data type can confuse discussions of LCA data quality. Accordingly, for purposes of these guidelines, data type is defined as the method used to generate LCA data.

TABLE 2-1. EXAMPLES OF LCA DATA SOURCES

Data Source	Example Source	Reference
Industry Reports	SRI Industry Reports	Stanford Research Institute
	Electric Utility Reports	Electric Power Research Institute
Trade Associations	Utility Company Database	Utility Data Institute
	American Iron and Steel Database	American Iron and Steel Institute
	Coke and Coal Database	American Coke and Coal Chemicals Institute
	Wood Database	Western Wood Products Association
Industry Databases	Chemical Industry Competitive Intelligence Database	Chemical Industry
	Energy Information Database	Energy Industry
	Coal Database	Coal Industry
	ECO Mine	Minerals and Mining Industry
Related LCIs/LCAs	Resource and Environmental Profile Analysis of Polyethylene and Unbleached Paper Grocery Sacks	Franklin Associates, Ltd., 1990
	Comparative Analysis of Selected Characteristics of Disposable and Reusable Towels	Barber et al., 1977
	Life-Cycle Analysis on PVC Packaging Systems	Cascone, 1992
	Resource and Environmental Analysis of High-Density Polyethylene and Bleached Paperboard Gable Milk Containers	Franklin Associates, Ltd., 1991
	Comparative Energy and Environmental Impacts for Soft Drink Delivery Systems	Franklin Associates, Ltd., 1989
	Environmental Effects of Different Packaging Systems for Fresh Milk	Mekel and Huppes, 1990
Government Documents/Reports/ Databases	*Monthly Energy Review*	Department of Energy (DOE)
	Annual Energy Outlook with Projections to 2010	DOE
	Manufacturers Energy Consumption Survey: Consumption of Energy 1988	DOE
	Minerals Facts and Problems	Department of Interior (DOI)
	Minerals Yearbook	DOI
	Minerals Commodity Summaries	DOI

continued

TABLE 2-1. EXAMPLES OF LCA DATA SOURCES (CONTINUED)

Data Source	Example Source	Reference
Government Documents/Reports/ Databases (continued)	Industry-Specific New Source Performance Standards	EPA
	Industry-Specific Water Effluent Guidelines and Water Quality Documents	EPA
	Toxic Release Inventory System	EPA
	Resource Conservation and Recovery Information System	EPA
	Treatment, Storage, Disposal, and Recycling (TSDR) Database	EPA
	Lifecycle Assessment Methodology: Data Needs and Development Task 1: Identification and Evaluation of Existing Data and Information	EPA (Draft)
	Lifecycle Assessment Methodology: Data Needs and Development Task 2: Evaluation of the Need to Develop New Information	EPA (Draft)
Journals/Papers/ Books/Reference Books	Journal of Air and Waste Management	Air and Waste Management Association
	Encyclopedia of Chemical Technology	Kirk-Othmer
	Metal Statistics	American Metals Market
	"Energy Flows in Industrial Processes"	Wall, 1988
	Handbook of Industrial Energy Analysis	Boustead and Hancock

Sources: RTI, 1992; SETAC, 1991; EPA, 1992; EPA, 1991a; and EPA, 1991b.

2.3 QUALITY ISSUES FOR LCA DATA

Data used in LCAs can be categorized as (1) primary, or (2) secondary, and (3) measured, (4) modeled, and (5) nonmeasured. Each data category and type can also be in different forms, i.e., aggregated or nonaggregated, and historical. The type, category, and form of data sources are not mutually exclusive. For example, a data source could be 10-year old estimated water emissions data for the facility under evaluation. If a data source falls into multiple categories, data quality problems could be compounded. The remainder of this chapter discusses data categories, types, and forms with respect to their potential impact on LCA data quality.

2.3.1 Primary Data

Primary data are plant-specific, measured, modeled, or estimated data. In most cases, primary data are preferred for use in LCAs because they are specific to the product or process being evaluated, and they are more amenable to assessing data quality concerns. To date, however, companies doing or commissioning LCAs have classified their primary data as proprietary. Under this circumstance, the data and the associated collection methods have been unavailable for review or simply not released in a publicly accessible manner. In some cases, summary results are made available but they do not include the actual plant-specific data. Consequently, verifying the quality of these data can be difficult. If an LCA involves the use of proprietary information, the associated data quality rests solely on the reputation of the company providing the LCA results. Despite these shortcomings, plant-specific data, which tend to be more representative of what is being evaluated and thus of higher quality, are recommended highly for use in LCAs.

Practitioners must be aware, however, that although plant-specific data generally have high quality, they are not always preferred to industry-based data as inputs for LCAs. Situations can arise where plant-specific data are less representative than aggregate industry figures. For example, a steel can manufacturer may buy steel on the metals market but may not be able to specify how or where the steel was manufactured. In this case, an LCA that used plant-specific manufacturing data may be less representative than data that reflect the mix of plants and processes that constitute the steel commodity market (ADL, 1993).

2.3.2 Secondary Data

Secondary data are those collected for a different purpose than the LCA being conducted. Secondary data sources are more complex to evaluate from a data quality perspective because they come in various forms and types, and typically lack explanation of the data collection methods and the variability in the data. Secondary data may be specific to a product or process under evaluation, or they may be aggregated industry data. In the latter case, the data may require some form of manipulation to generate values suitable for use in LCAs (see discussion below on aggregated data). Based on these concerns, it is recommended that, where possible and appropriate, primary data be used in LCAs. When primary data are unavailable, practitioners may have no other option but to use secondary data to fill in LCA data gaps.

2.3.3 Measured Data

Measured data are monitored or sampled data, or data generated from a census or a survey. These data can be collected under statistically based or nonstatistically based protocols. As indicated above, measured data can also be either primary or secondary in nature. In addition to the concerns expressed above regarding primary and secondary data, measured data present the following potential data quality problems. Monitored or sampled data could be inaccurate due to the use of an inappropriate sample size, bias in the monitoring or sampling devices, improper equipment calibration, or the continuous misreading of measurement instruments. Problems with survey or census data could be due to an inappropriately worded question, or some other flaw in the survey or statistical protocol.

For primary data, the problems identified above can be minimized by carefully designing an experiment, or using proper statistical procedures when employing measurement and/or monitoring techniques. If primary data are collected for use in an LCA, practitioners may want to consult a statistician to help determine the appropriate sampling design and methods. For secondary sources, however, to understand the problems associated with measured data, it is important, at a minimum, to have a description of the data collection methods, or the statistical protocol. If a description of the data collection methods is available, practitioners should consider consulting a statistician to assess their validity.

2.3.4 Modeled Data

Practitioners use models to generate data for LCAs, or they may rely on secondary sources that use a model to generate the data. Models can be used to simulate an industrial process, or estimate emissions from a production process. The potential shortcomings associated with "modeled data" primarily pertain to how the model was constructed. To have confidence in simulated data, models should be both verified and validated. Verification entails determining whether the model provides the correct output. Validation techniques include using expert opinion to determine whether the model presents an adequate representation of the process, or exercising the model to reproduce an historical data set. A model that is not validated and verified may produce apparently useful results that have very little relation to what is actually being modeled.

It is easier to verify and validate primary rather than secondary modeled data. With respect to primary data, practitioners should have access to their own models to assess the accuracy of the results. Secondary data sources, however, may neither provide the full model, which would enable a user of the material to assess the accuracy of the model and the associated results, nor include information regarding the author's verification and validation activities. If this, or similar, information is unavailable in secondary data sources, practitioners may have difficulty determining the accuracy of the model results.

2.3.5 Nonmeasured Data

Examples of nonmeasured data include plant-specific estimates or educated guesses and data sources such as EPA's TRI (Toxic Release Inventory) database which contains data collected annually on a certain segment of the chemical manufacturing industry pursuant to a legal reporting requirement.

Nonmeasured data sources pose several potential problems. The data may be aggregated and thus contain the shortcomings outlined in the aggregated data section below. More importantly, however, many nonmeasured data sources describe neither the methods used to collect or estimate the data nor whether mathematical, or other, techniques were employed to compensate for missing data and data deficiencies. Assessing the quality of these data requires reviewing the evidence and assumptions that went into deriving the value(s). Without sufficient understanding of how and why the data were collected, an analyst could make biased inferences using the data. Unless experts who developed the data can be consulted, or there is adequate peer acceptance of the data source, the analyst may be unable to determine the extent of potential bias.

2.3.6 Aggregated Data

Aggregated data typically are presented as summary reported values. An aggregated data set usually does not list the intermediate values that went into compiling the data. The data aggregation process can eliminate valuable information (e.g., variability in the data) needed to evaluate the quality of a data set. Consequently, the quality of aggregated data can be more difficult to assess than nonaggregated data.

Aggregated data also may require some sort of manipulation (e.g., interpolation, extrapolation, or back calculation) to generate a value suitable for use in LCAs. Any uncertainty associated with the aggregated data could be compounded by the method used to produce appropriate LCA data values. For example, the *DOE Monthly Energy Review* contains a section with monthly and yearly totals for residential and commercial, industrial, transportation, and utility energy consumption. Within each class of end users, the data are broken down by the type of fuel used to generate the energy. To use these data to perform an LCA on a product (e.g., tires), an analyst would have to make assumptions about the percentage of industrial energy consumption used in tire production, the percentage of tire production attributed to each plant, and the percentage of fuel used to generate energy for each plant. These percentages may be estimated by using expert opinion/knowledge or based on a mathematical model. The level of uncertainty in the aggregated consumption values could be compounded by the uncertainties associated with any assumptions used in modifying the data.

Nonaggregated data may or may not provide further information to assess data quality. On one hand, nonaggregated data can be used to calculate such statistical measures as the mean, standard deviation, and skewness which may provide an indication of the central tendency and total variability in the data set. On the other hand, nonaggregated data may be composed of inputs from different plants within the same company. Differences in the data could be due to the way the parameter was measured (e.g., direct measurements, statistical sampling, engineering estimates, modeling, etc.), the different operating characteristics of the plants (e.g., fuel and raw material mixes, regulatory requirements, etc.), or the period of measurement (episodic, continuous, random sampling, daily/monthly/annual, etc.). Under this scenario, nonaggregated data may provide no additional useful information unless the other sources of variability also are discussed.

2.3.7 Historical Data

Problems with historical data mainly concern the age of the data set. In determining the age of a data set, the analyst should be concerned with the actual date the data were generated, not simply the date of publication. For example, emissions data published in 1983, could have been generated in 1981. These data would be 11 years old in 1992, not 9 years old. Older data may not be representative of a current situation because a process may have changed significantly since the data were compiled. There is no benchmark to determine whether a data set is too old. By reviewing the history of the process and potential plant modifications, the analyst can assess whether the age of the data is or is not an issue.

CHAPTER 3
INCORPORATING DATA QUALITY INTO LIFE CYCLE ASSESSMENTS

The LCI is the initial data generation and collection component of an LCA. As such, the quality of data used in an LCI directly affects the results of an LCA. SETAC (1990) and EPA (1992b) have prepared key LCA documents that outline the stages of an LCI. SETAC and EPA indicate that an LCI should include data on:

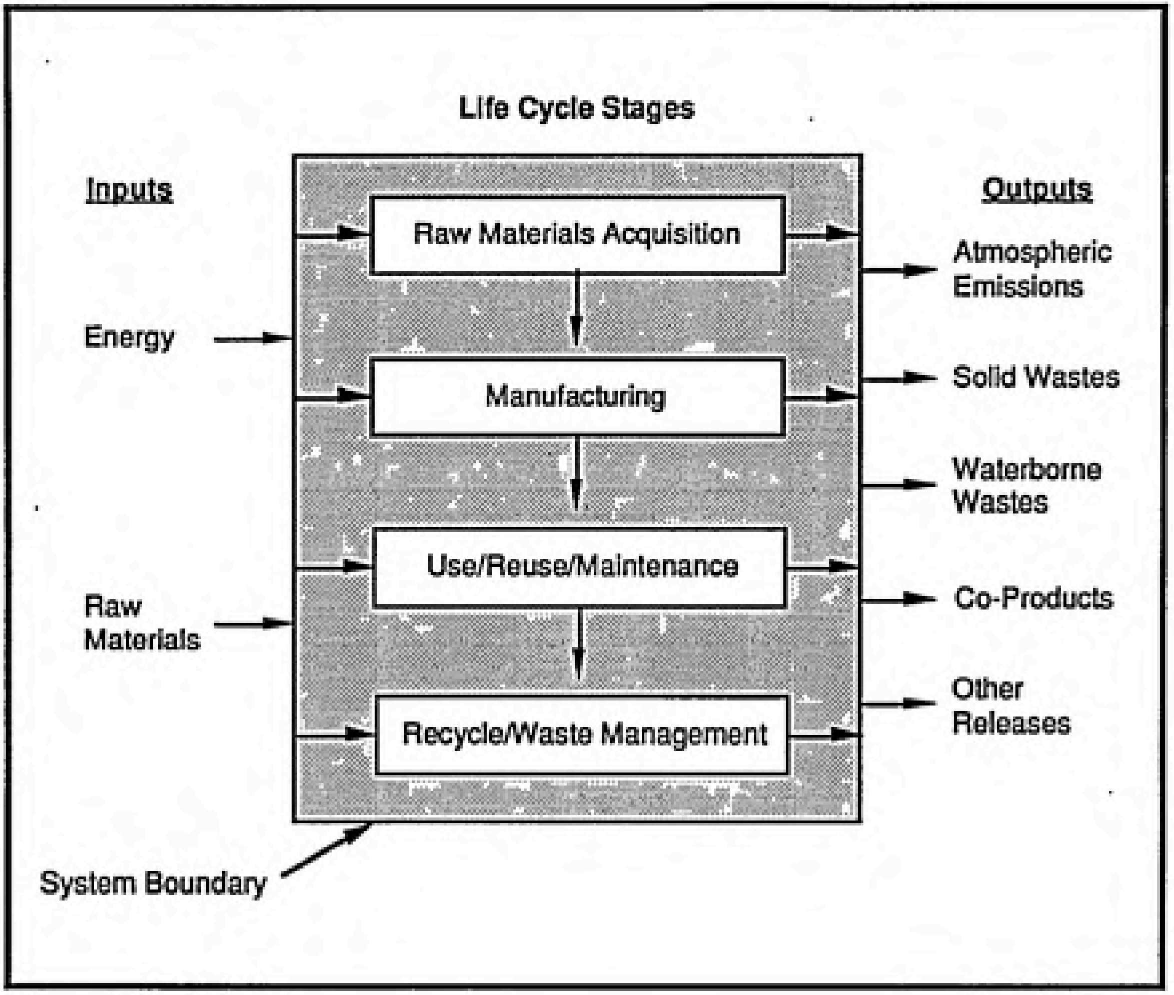
- raw materials acquisition,
- manufacturing (which includes material manufacture, product fabrication, and filling/packaging/distribution,
- use/re-use/maintenance, and
- recycling/waste management.

Each stage of a life cycle receives inputs such as energy and raw materials and produces outputs such as waste streams (air, water, and solid/hazardous waste), recyclables, co-products, and final, or usable, products. Figure 3-1 shows the life cycle stages for an industrial process.

Figure 3-2 outlines the steps necessary to develop the inventory of data used to conduct an LCA. In addition to providing a framework for building a data base of life cycle data, Figure 3-2 identifies those points in the process where data quality should be considered. The following sections discuss each step in the inventory development process and its relation to an evaluation of LCA data quality.

3.1 DEFINE THE SCOPE OF THE LCA

Defining the scope of the study is the first step in conducting an LCA. During this phase, practitioners should define the product, process, or activity under evaluation. Important considerations include identifying whether the study will be for internal use (within a company) or for external use, whether it will be absolute or comparative (evaluating one product or process versus multiple products or processes), and what the end use of the analysis will be.



Source (EPA, 1992b)

Figure 3-1. Life Cycle Stages for Industrial Processes

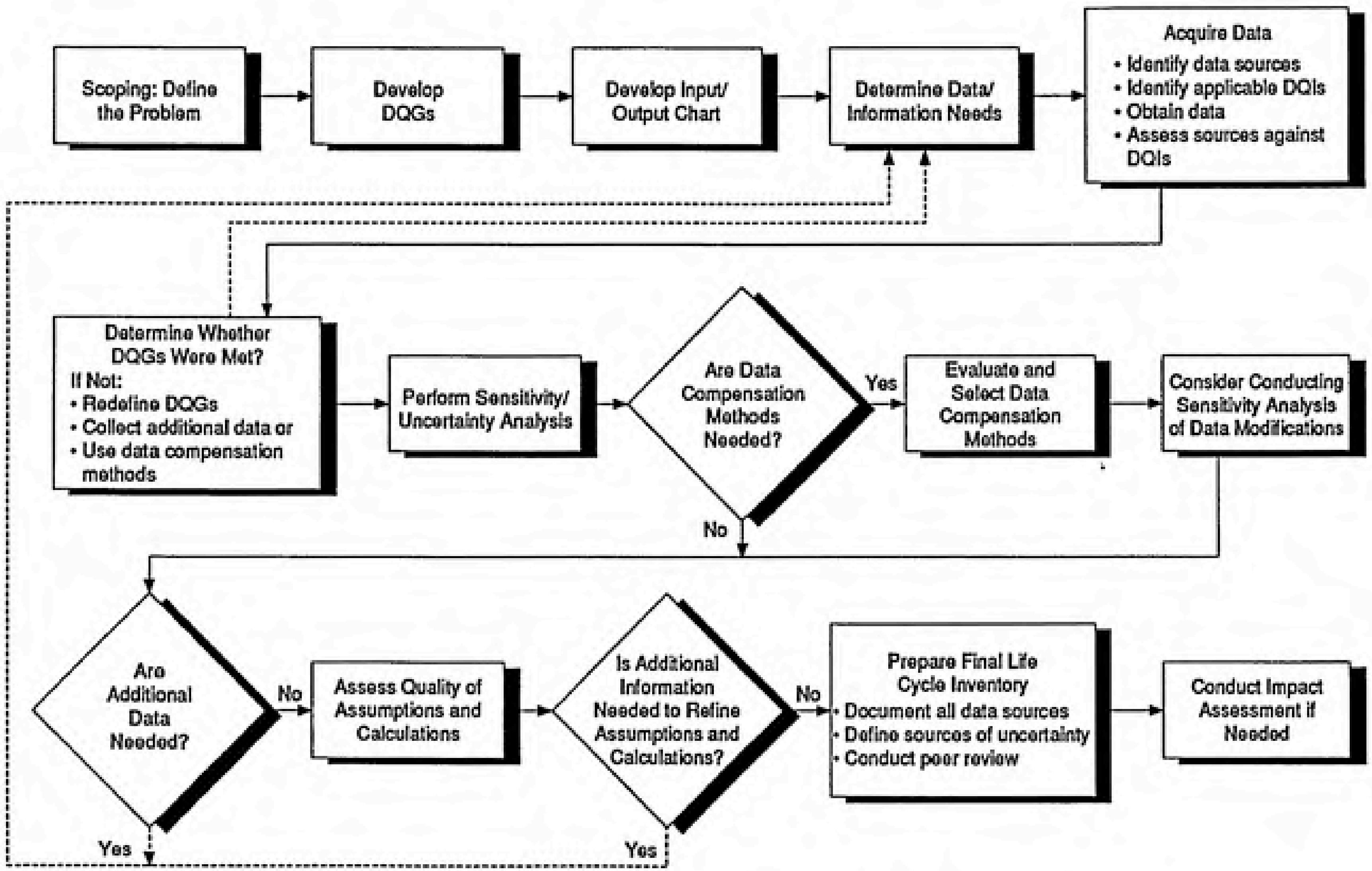


Figure 3-2. LCA Data Development Steps

Practitioners should also consider data quality as they define the scope of an LCA. They should consider the type of data needed for the analysis and the level of data quality necessary to support the intended purpose of the LCA. In addition to defining the overall purpose of the study, practitioners should determine, from the outset, the steps and level at which they intend to stress data quality. With respect to data quality, practitioners should ask the following questions when defining the scope of the LCA:

- Will the data be used for an inventory only, or will they be used to conduct an IA?
- What type of decision will be made using the data, e.g., modifying a product or an industrial process, imposing a regulation, or comparing one product to another?
- Can data commensurate with the scope of the study be acquired given the available resources?

3.2 DEVELOP DATA QUALITY GOALS (DQGs)

In addition to defining the scope of an LCA the analyst should define the level of data quality that will be sufficient to support the study's purpose given available resources. Data quality goals (DQGs) are specifications for the adequacy of data used in an LCA, or for certain LCA parameters used in an analysis. DQGs provide a framework for balancing available time and resources against the quality of the data required to make a decision or statement of overall environmental or human health impact (EPA, 1986a). Practitioners should use DQGs as performance criteria (i.e., where data quality will be stressed in the analysis) and measure their achievement by a documented, systematic evaluation of data quality indicators (DQIs).

Chapter 4 provides a more detailed discussion of DQGs.

3.3 DEVELOP INPUT/OUTPUT CHART

After clearly defining the scope of the LCA, and the acceptable level of data quality, an LCA analyst should delineate the system with appropriate boundaries. This information is typically provided in an input/output chart or matrix, which identifies all inputs of materials to and outputs from an industrial process (see Figure 3-3). The parameters needed for an LCA have been thoroughly discussed in the SETAC (1990) and EPA (1992b life cycle documents. Those reports simply state that all inputs (energy, raw materials, and water, etc.) and the outputs (air, waste, water, recyclables and usable products, etc.) of the industrial process under evaluation must be clearly identified. It is

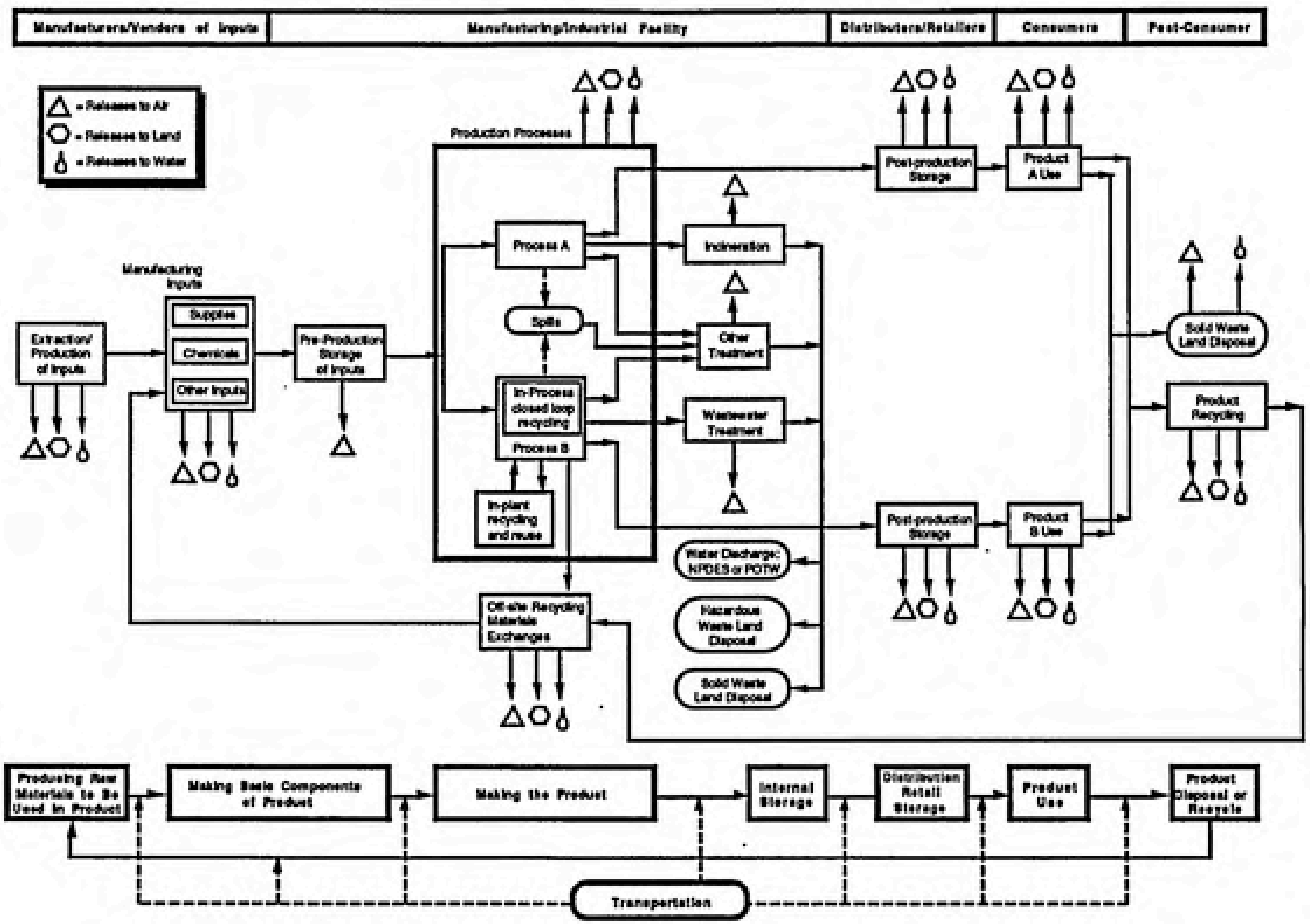


Figure 3-3. Example Product Life Cycle Input/Output Chart

important to note, however, that an LCA should indicate clearly where—and why—system boundaries have been drawn. It is possible for LCAs on similar processes to have different results, not due to differences in data quality, but due to where practitioners drew the boundaries of the analysis. If practitioners clearly identify the boundaries of their analysis, LCA results will be more transparent to users of the material.

3.4 DETERMINE DATA/INFORMATION NEEDS

The analyst's next step is to determine the appropriate data needs based on both the input/output matrix and the scope of the LCA. The input/output matrix, in combination with the appropriate system boundaries, defines the data necessary for a complete inventory. The matrix identifies the inputs and outputs of the process being inventoried, and the secondary processes—those not directly involved in the production of the product such as energy and transportation—for which data may also need to be collected. The scope of the LCA also may affect the overall data needs. For example, an analyst especially interested in air emissions may decide to put less emphasis on data quality (e.g., use estimated rather than measured data) for non-air releases. This lessened emphasis should be reflected in a statement of the LCA's purpose and the associated DQGs.

3.5 ACQUIRE DATA

The data acquisition phase includes five parts:

- identifying the appropriate data sources,
- obtaining the data,
- identifying applicable DQIs,
- assessing the data sources against the DQGs and DQIs, and
- collecting additional data, if necessary.

Numerous data sources are available for building an LCA database (see the discussion of LCA data sources in SETAC (1990) and EPA (1992b) life cycle assessment documents). EPA also expects to release in 1993 two documents that review data sources applicable to LCAs (EPA, 1991a and 1991b). Chapter 2 of this document also identifies applicable LCA data sources.

The data acquisition phase is an important point in the inventory process for assessing the quality of data sources. Most LCAs conducted to date have used a mix of primary and secondary data. Assessing the quality of secondary data sources is difficult, particularly because they typically do not contain raw data, statistical information, or other information that could be used to determine data quality. Regardless of the level of difficulty, at this point in developing the inventory, the analyst should make an effort to determine the quality of the data source, be it primary or secondary. The results of such an analysis can be used to indicate the uncertainty associated with various study parameters and, based on available resources and the importance of the data component, whether additional data sources should be consulted.

The next step is to select applicable DQIs. DQIs are qualitative and quantitative measures used to evaluate data quality. Examples of DQIs include accuracy, age, representativeness, and precision. The analyst should select DQIs that correspond to the data source (primary or secondary) and how the data will be used in the inventory. If data from a secondary source are going to be used in an LCA, the analyst may need to interpolate, extrapolate, or back-calculate the data. For example, suppose an analyst has DOE energy consumption data for a particular industry, with the DOE data representing total domestic consumption by utilities for different energy sources, such as coal-based electricity. To determine the appropriate value that can be used in an LCA (i.e., for a facility or group of facilities), the analyst may need to back-calculate from the DOE aggregated data. If this is the case, the analyst will rely on his or her knowledge of the process to make the necessary assumptions and calculations. Under this scenario, different DQIs will be necessary to assess not only the quality of the data source, but also the assumptions and calculations used by the analyst to generate LCA data values.

LCAs use various types of data, such as modeled, statistical, or nonmeasured data. Different DQIs also may be selected depending on the form of the LCA data. For example, data generated through a statistical analysis could be evaluated in terms of whether a QA/QC process was used to generate the data, whereas data generated through models could be evaluated based on whether the model was verified and validated. Wholly different quality issues arise with nonmeasured data, such as whether the data source is widely accepted by peers or colleagues in the field.

The above discussion is written from the perspective of the practitioner conducting the LCA data quality evaluation. However, data quality evaluations can also be conducted by analysts reviewing existing or published LCAs. In addition to the DQIs described above, analysts reviewing existing LCAs may need to consider whether the data are accessible, reproducible, and referenced.

Chapter 4 provides a detailed discussion of the DQIs that are applicable to different types and forms of data used in LCAs.

3.6 DETERMINE WHETHER DQGS WERE MET

Once data sources have been identified and assessed against all applicable DQIs, it is appropriate to determine if the source meets the DQGs set after the scope of the study was defined. If the DQGs are not met, practitioners have three options, they can:

- redefine their DQGs,
- collect additional data, or
- apply available and appropriate data compensation methods to fix problems with the data.

This stage of the process stresses the iterative nature associated with setting and adhering to DQGs.

3.7 PERFORM SENSITIVITY/UNCERTAINTY ANALYSIS

Evaluating the impact of different parameters on LCA results is important. For an inventory, sensitivity analysis and, to a lesser extent uncertainty analysis, may be used to evaluate these effects. Sensitivity analysis is used to examine the effects of changes in inputs on model outputs (Morgan and Henrion, 1990; and Clemen, 1991), whereas uncertainty analysis is used to evaluate the importance of input uncertainties with respect to their relative contribution to the uncertainty in model outputs, or results (Morgan and Henrion, 1990; Vesely and Rasmuson, 1984; EPA, 1985; and Finkel, 1990). If an analyst knows which inputs have the greatest impact on system outputs, he/she can prioritize parameters in terms of their necessary data quality. For example, if a sensitivity analysis shows that waste generation does not change due to modifications in energy values (i.e., energy would be considered an insensitive parameter), the analyst could place less concern on the quality of energy data. In other words, the results of sensitivity analyses could identify where resources should be directed such that data quality is maximized for the most "important" system parameters.

Uncertainty analysis may serve two purposes in an LCA. First, if parameters identified as most important (or sensitive) to LCA results also are highly uncertain, a large benefit would be derived by focusing data quality resources on these parameters. Second, this technique, which includes such processes as error propagation, could be used to estimate the uncertainty in overall LCA results.

Chapter 6 provides a more detailed explanation of applications of sensitivity analysis to LCA data.

3.8 EVALUATE AND SELECT DATA COMPENSATION METHODS

An inventory could be missing pieces of data or contain data with gaps or deficiencies for a particular industry, facility, product or process. For example, data derived from surveys may be missing due to nonresponse by facilities receiving the survey (unit nonresponse) or missing data for specific items on a questionnaire (item nonresponse) (Lepkowski et al., 1987). The analyst may have identified these problems during the previous evaluation of data quality. This step involves evaluating various data compensation methods, such as imputation (e.g., proxies, deductive imputation, random imputation overall, and hot-decking), different weighting methods, and meta-analysis and selecting the approach most applicable to adjust for deficient data in the inventory.

Data compensation methods are mathematical techniques that can be used to replace missing data and adjust for data deficiencies. Although these techniques are generally acceptable, they do not replace collecting additional, more applicable data. Imputation and weighting methods typically do not reduce the variability in the data set. Some forms of imputation, however, can reduce the variability of the data set and, hence, provide a false sense of precision. These techniques likely are best applied to the parameters that a sensitivity analysis shows to be less important to the inventory. However, their use should be reviewed with statisticians familiar with relevant data compensation methods.

Compensating for missing data or data deficiencies may not be necessary in all cases. After performing sensitivity analyses, the analyst has the choice of correcting for problems with the data or moving forward to assessing the quality of any assumptions or calculations used to develop values for data in the inventory.

Data compensation methods are discussed in more detail in Chapter 7.

3.9 ASSESS IMPACT OF DATA MODIFICATION

If quantitative measures have been used to compensate for data gaps, deficiencies, or missing data, the impact of this modification should be evaluated. If sensitivity analysis has been used, the analysis could be repeated to determine whether modifying the data changes the results of the analysis.

3.10 COLLECT ADDITIONAL DATA, IF NECESSARY

The collection of data may be done on an iterative basis. After evaluating a data source against the selected DQIs, an analyst may decide to consult additional data sources. The results of sensitivity analyses also may indicate where additional data may need to be collected.

3.11 ASSESS THE QUALITY OF ASSUMPTIONS AND CALCULATIONS

Data used in LCAs may often come from secondary sources, such as government reports/databases or aggregated industry data, rather than actual data from monitoring the process of interest. In many circumstances, secondary data may not be in a form that can be used directly in an LCA. For example, an often-used source of energy consumption information is DOE's *Annual Energy Review*. These data are aggregated for all utilities that consume various sources of energy. To determine the energy consumption for a particular facility or industry based on this information, a number of assumptions and calculations may be necessary to calculate an ultimate value suitable for an LCA. In cases such as this, data quality must be considered not only with respect to the data source, but also with respect to the assumptions and calculations used to generate LCA data values. Chapter 4 describes the DQIs used to evaluate assumptions and calculations.

3.12 ACQUIRE ADDITIONAL INFORMATION TO REFINE ASSUMPTIONS AND CALCULATIONS, IF NECESSARY

Based on the results of evaluating assumptions and calculations against the chosen DQIs, the analyst may determine that his/her knowledge of the process was insufficient to develop adequate assumptions and subsequent calculations. Under these circumstances, additional information may need to be acquired to refine the assumptions and calculations. No matter how good a secondary data source is, the data would be of limited value if poor assumptions and calculations are applied.

3.13 PREPARE FINAL LIFE CYCLE INVENTORY

A final inventory should include explicit information regarding the quality of the data and assumptions used throughout the report. An LCA should include a review of the appropriate sources against the applicable DQGs and DQIs. Similar results should be included for the review of the assumptions and calculations employed when the data could not be used directly in the inventory. This information will provide an indication, and allow for an outside assessment, of overall data quality.

To the extent possible, the sensitivity and uncertainty associated with each important parameter (or class of parameters) used in the analysis also should be reported. In addition to indicating data quality, the report should identify the degree of variation in each parameter. This information is important to understanding the total variability in the results, regardless of whether it will be used solely as an inventory or as part of an IA.

3.14 CONDUCT PEER REVIEW

Peer review is an important aspect when publishing any type of study, technical or nontechnical, that is used to state a position, advocate a point, or make a decision. Peer review typically is used in scientific fields and is increasingly being applied to the field of policy analysis (Morgan and Henrion, 1990). Peer review is equally important for assessing LCA data quality. Data typically come from disparate sources with multiple problems and are combined to fit into the LCA framework. This process involves creativity, expert judgment, and many assumptions. Opening an LCA to peer review to include an assessment of data quality will provide the LCA external credibility.

Practitioners conducting external LCAs should consider distributing the analysis for peer review. However, if the LCA is for internal use only, it may be unnecessary to peer review the document based on issues of confidentiality and cost.

3.15 CONDUCT IMPACT ASSESSMENT (IA)

Practitioners base LCA results on inventory data only, or on the application of environmental and human health impact assessment methodologies to the data collected in the inventory. IAs are concerned with determining such criteria as the number of deaths or sicknesses, or the extent of contamination or exposure, caused by the release of potentially harmful pollutants or materials. This contrasts with using inventory data to simply assess the magnitude of outputs due to various inputs. Conducting an impact assessment typically involves using a range of models and analytical methodologies, such as fate and transport models, health impact assessment models, dose-response models, and uptake models, which tend to require the use of plant- or site-specific data rather than aggregated data. Based on the criteria and models used to conduct IAs, this phase of an LCA may dictate the type of data needed in the inventory. This does not imply, however, that one phase of an LCA calls for higher or lower data quality than another. Rather, given a practitioners available time and resources, each phase of an LCA should use data of the highest quality possible.

CHAPTER 4
DATA QUALITY GOALS AND DATA QUALITY INDICATORS

This chapter and Chapter 5 provide a framework for assessing LCA data quality, which can be used by LCA practitioners, analysts working to develop and improve LCA methodologies, and users of LCAs. There are three aspects to this task. First, as with any analysis using environmental data, data quality goals (DQGs) must be set that define the level of data quality sought in the overall analysis, or in individual parameters used in the analysis. Second, benchmarks, typically referred to as data quality indicators (DQIs), must be identified and used as measures of whether the DQGs have been met. Third, the results of this analysis must be documented in the final analysis. This procedure parallels closely the traditional quality assurance/quality control process used to evaluate the quality of primary environmental data (See Appendix A).

DQGs and DQIs are discussed in this section. Sections 4.1 and 4.2 explain and define the concepts behind these terms in the context of evaluating LCA data quality. Sections 4.3, 4.4, and 4.5 discuss specific DQIs that can be applied to an assessment of LCA data quality. Where possible, examples have been provided to make the information more accessible to LCA practitioners and analysts. Chapter 5 provides a framework for applying DQGs and DQIs to an assessment of LCA data quality and a mechanism for translating this information into LCA data quality worksheets and an overall data quality matrix.

4.1 DATA QUALITY GOALS (DQGs)

LCA is a methodology used to evaluate environmental releases and resource consumption and the consequent environmental and human health impacts associated with a product, process, or material. Results from these analyses are used for a variety of purposes: by companies internally for decision-making, externally for communicating information about a product or advocating or promoting one product over another; and by government agencies for policy and/or regulatory decision-making. To have confidence in LCA results, it is necessary that analysts consider and evaluate the quality of the data used in the analysis.

Data quality goals (DQGs) are specifications for the adequacy of data used in an LCA, or for certain LCA parameters.

An important first step in a data quality evaluation is defining data quality goals. As indicated in Chapter 3, once the scope and boundaries of an LCA have been determined, DQGs should be enumerated. DQGs are specifications for the adequacy of data used in an LCA, or for certain LCA parameters. DQGs serve two primary purposes:

- structuring an approach for data acquisition, and
- serving as data quality performance criteria (e.g., data are evaluated against DQIs to determine whether DQGs have been met).

DQGs are qualitative statements that indicate the level of confidence required in the input data to support LCA results. DQGs should identify the level of data quality sought for the overall analysis, or for individual parameters used in the analysis. There is no required number, or standard set, of DQGs for an LCA. Rather, given the scope of the study, practitioners should determine the number of DQGs necessary for the LCA and then tailor them accordingly. Examples of DQGs include:

- approximate data values are adequate for the energy data category,
- obtain air emissions data within a given range with 90 percent confidence, and
- use certified primary data for the recycling/re-use data category.

Defining and applying DQGs in an LCA data quality evaluation is a subjective process. However, if DQGs are defined prior to assessing the quality of data sources, they will help increase the clarity and transparency of LCAs. If LCA practitioners define the scope of their analyses and the accompanying DQGs, two benefits will result: a structure will be imposed that enables data to be quality controlled prior to its use in an LCA, and users of the analysis will have sufficient indication of where the LCA gave priority to data quality. LCA practitioners should make it a regular practice to report in detail the objectives of the LCA and the related DQGs.

4.2 FACTORS AFFECTING THE CHOICE OF DQIs

After defining DQGs for an LCA, practitioners should specify which data quality indicators (DQIs) will be used to evaluate LCA data quality. DQIs are the cornerstone of any data quality assessment methodology. They are benchmarks against which data quality can be assessed to ensure that the DQGs have been achieved. The identification and analysis of DQIs helps to determine the level of confidence an analyst can have in the data.

Data Quality Indicators (DQIs) are data characteristics that serve as benchmarks against which data quality can be assessed to ensure that DQGs have been achieved.

An important aspect of assessing LCA data quality is determining which DQIs are most applicable to the analysis. The selection of LCA DQIs is influenced by:

- the form of the data (i.e., whether the data are primary or secondary);
- manipulations made to the data (i.e., whether the data are modeled, nonmeasured, or extrapolated, interpolated, or back calculated); and
- the type of data quality analysis being conducted (i.e., whether data quality is being assessed during the conduct of the LCA, or by an analyst reviewing an existing LCA).

Data Form

Data used in LCAs come from a variety of sources. On a general level, LCA data can be classified broadly as either primary or secondary. Primary data are facility-specific, measured, monitored, or non-measured data. Primary data, for example, can be measured pursuant to statistical or non-statistical protocols, nonmeasured through estimates or educated guesses, or generated from models (see Figure 4-1).

Secondary data are those collected for a purpose other than the LCA being conducted. These data are more complex to evaluate from a data quality perspective because they come in multiple forms, and typically lack explanation of the data collection methods and the variability in the data. Like primary data, secondary data can be measured pursuant to statistical or non-statistical protocols, or generated from models. Secondary data can also be compiled for a variety of purposes where the collection procedure is neither statistically based nor reliant on models. An example is EPA's Toxic Release Inventory (TRI), which contains chemical release data on approximately 300 chemicals manufactured, produced, and used by certain companies in SIC codes 20 through 39. These data, for example, may be based on educated guesses or engineering estimates. Throughout this document, this latter group of secondary data is referred to as non-measured data (see Figure 4-1).

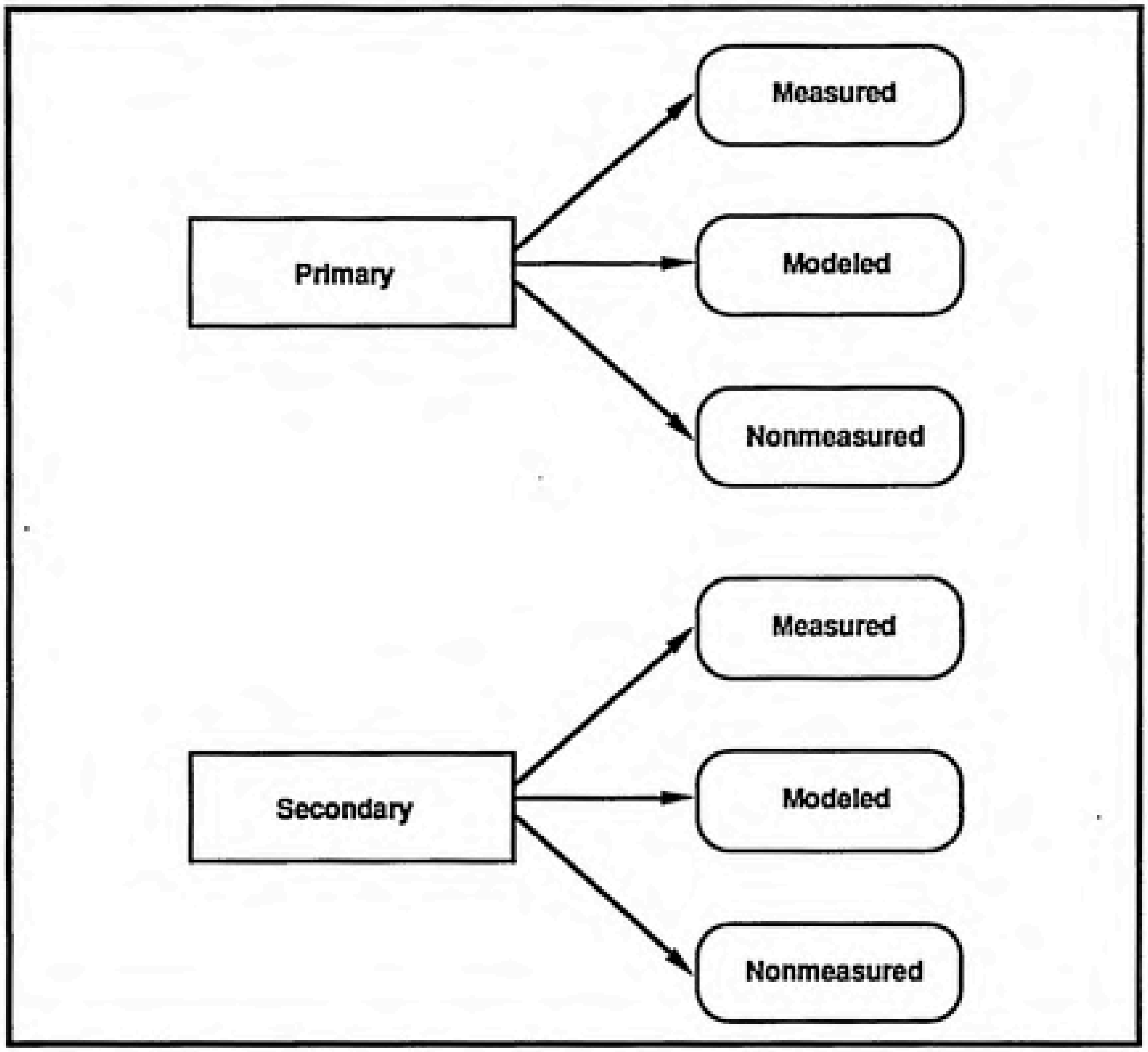


Figure 4-1. Form of Data Typically Used in LCAs

Traditional indicators of data quality include precision, accuracy, bias, and completeness (EPA, 1991; and Johnson and Ford, 1986). These DQIs generally are quantitative measures used to evaluate primary data. Although these DQIs can be used to evaluate secondary data, other indicators also need to be assessed. Additional DQIs appropriate for secondary data include, but are not limited to, determining whether:

- the data source is considered acceptable by peers or colleagues in the field;
- the data collection methods are described or obtainable; or
- the limitations associated with the data have been enumerated.

In short, because secondary data typically are not generated under statistical guidelines, analysts must use other approaches to understand the data collection procedures, the purpose of the data, and the variability and limitations associated with the data.

Data Manipulations

As discussed above, data quality is influenced by the quality of the data sources used in the analysis. Data quality, however, is also influenced when assumptions and calculations are used to generate data suitable for use in LCAs. The quality of a data source may be found superior but, if the data are manipulated, poor assumptions and/or calculations could result in the use of inappropriate data values.

Both primary and secondary data used in LCAs may be subject to such influences. If the data are manipulated for use in an LCA, it is imperative to assess not only the quality of the data source, but the assumptions and calculations used to generate the LCA data values. A different combination of DQIs should be evaluated when assessing the quality of calculated data where the assumptions and associated calculations can influence the data values used in an LCA. For example, assumptions could be measured against the bias, representativeness, and completeness DQIs, and calculations could be measured against such DQIs as precision, limitations enumerated, and documentation provided.

Type of Data Quality Analysis

The type of data quality analysis being conducted also influences the selection of DQIs. There are two types of LCA data quality evaluations: those conducted by the practitioner while developing an LCA, and those performed by analysts reviewing existing and/or published LCAs. The DQIs defined in the following pages can be used for both types of data quality evaluations.

Most LCAs have addressed data quality in a rudimentary fashion. Without appropriate references and basic information about the data, it is difficult to assess the quality of the data "after the fact." To accommodate these concerns, analysts should use additional DQIs to evaluate published or released LCAs. These include whether the data have been referenced, and whether the data are accessible and reproducible.

The remainder of this chapter defines 17 DQIs that are appropriate for evaluating the quality of data used in LCAs. The DQIs are divided into two types: quantitative and qualitative DQIs. Table 4-1 provides a brief description of the 17 DQIs and indicates their application to an evaluation of LCA data quality.

Although the DQI list is comprehensive, it may not be exhaustive. Moreover, different practitioners may use different terms to describe similar data characteristics (e.g., consistency versus bias). Accordingly, it is acceptable for practitioners to add, subtract, or redefine certain LCA DQIs.

4.3 QUANTITATIVE DQIs

4.3.1 Precision

Precision refers to the closeness of estimates to each other or, in other words, the variability in a set of values or measurements compared to the mean. The sample standard deviation and the coefficient of variation (CV) (i.e., the standard deviation divided by the mean) are indicators of precision. The smaller the standard deviation and the coefficient of variation, the better the precision (EPA, 1984; EPA, 1985; EPA, 1990; and EPA, 1991).

Precision typically is used to evaluate measurement methods used for collecting environmental samples. For any measurement method, sources of variation include sample collection, handling, shipping, storage, preparation, and analysis. Generally, precision is measured by using a reference chemical sample with an assumed concentration, e.g., 50 parts per million (ppm), which is identified as "T" in Table 4-2 below. The sample is then analyzed a number of times, e.g., obtaining values of 48, 55, 50 and 45 ppm, compared against the reference chemical sample, and a coefficient of variation is calculated. These values allow for an assessment of the variation in the measurement device. Table 4-2 provides sample data from four measurements that illustrate how precision and bias are calculated (see below for a discussion of the bias DQI). Based on the data provided in Table 4-2, the standard deviation is 4.2 and the CV is approximately 0.085 (EPA, 1984).

The precision DQI can be applied to certain LCA data. This DQI is most applicable to an analysis of the measurement methods used to collect primary data. For example, the precision DQI could be used to evaluate the variability in a measurement device used to determine air, water, or waste releases. The variability would be measured by calculating the mean, standard deviation, and the coefficient of variation. Similar

TABLE 4-1. APPLICATION OF DQIs TO PARAMETERS THAT IMPACT DATA QUALITY

DQI	Definitions	Form of Data				
		Measured	Modeled	Nonmeasured	Assumptions	Calculations
Accessibility[a]	The data source can be easily obtained.	●	●	●	●	●
Bias	Systematic error where data values are consistently higher or lower than a corresponding true parameter(s).	●	●	●	●	
Comparability	The degree to which different methods, data sets, or decisions, agree or can be represented as similar or equivalent.	●	●	●		
Completeness	The amount of data obtained compared to the amount of data needed.	●	●	●	●	●
Data Aggregation (secondary data only)	Degree of disaggregation, e.g., the information exists to determine the variability in the data and/or trends or relationship between facilities or industries.	●	●	●		
Data Source Acceptability (Secondary Data Only)	The dependability of the data source, how widely it is accepted by colleagues in the field or based on peer review.	●	●	●	●	●
Description of Data Collection Methods (Secondary Data Only)	Data source includes description of how the data were collected and basis for the data collection effort.	●		●		
Limitation of Data Collection Methods Enumerated (Secondary Data Only)	Data source identifies the sources of variability in the data set.	●		●		
Model Documentation Provided	Data source provides information that clarifies the uncertainty associated with individual parameters and the model in total.		●			●
Model Limitations Enumerated	Data source provides information that clarifies the uncertainty associated with individual parameters and the model in total.		●			●
Precision	The variability in a set of values or measurements compared to the mean.	●	●	●		●
Referenced[a]	The data source has been appropriately cited.	●	●	●		
Representativeness	The degree to which the data accurately and precisely describe what an analyst is trying to describe.	●	●	●	●	
Reproducible[a]	Enough information and data are provided to permit an independent researcher to reproduce the study.	●	●	●		●
Statistical Measures Provided/Calculable	Data source provides measures for, or has the data in a format that permits the calculation of, the mean, standard deviation and/or skewness.	●	●	●		
QA/QC (Primary Data Only)	EPA's quality assurance/quality control protocol was used to collect data through sampling and analysis.	●				
Validation/Verification	Refers to whether the data source, and a model particularly, has been checked for errors, and evaluated against an accepted method or standard.		●			

[a]Additional DQIs to apply when evaluating an existing or published LCA.

TABLE 4-2. SAMPLE DATA TO CALCULATE PRECISION AND BIAS

Measurements	X_i	$X_i - \bar{X}$	$(X_i - \bar{X})^2$
1	48	1.5	2.25
2	55	5.5	30.25
3	50	0.5	0.25
4	45	-4.5	20.25

$$\text{Average } \bar{X} = (X_1 + X_2 + X_3 + X_4) \div n = (48 + 55 + 50 + 45) \div 4 = 49.5$$

$$\text{Variance } S^2 = \sum_{i=1}^{4} (Xi - \bar{X})^2 \div (n-1) = (2.25 + 30.25 + 0.25 + 20.25) \div 3$$

$$S^2 = \frac{53}{3} = 17.67$$

$$S = 4.2$$

$$\text{CV} = \frac{S}{\bar{X}} = \frac{4.2}{49.5} = 0.085$$

$$\text{Bias} = \bar{X} - T = 49.5 - 50 = -0.5$$

$$\text{Percent Bias} = \frac{\bar{X} - T}{T} \times 100 = \frac{49.5 - 50}{50} \times 100 = 1.0\%$$

Source: EPA, 1984

calculations could be performed for primary data generated with a model. This DQI could also be applied to statistically generated secondary data if it is possible to calculate the standard deviation and the CV. Comparing these values against the mean would provide an indication of the degree of variability in the data.

The application of the precision DQI is less clear for secondary data that are modeled or nonmeasured. With respect to modeled data, the precision DQI could be applied if three pieces of information are provided: the full data set, the model documentation, and a reference value. If this information is unavailable, model precision could be determined based on expert opinion. An expert, or group of experts, could be consulted to determine the degree of variability in the data and whether the variation is acceptable.

The application of the precision DQI to non-measured data, such as the TRI database, or a DOE total energy consumption value, is even less clear than for modeled data. A possible application of the precision DQI to these data would be evaluating the data in a time series and determining if the year-to-year variation is reasonable. For example, the TRI database could be evaluated to obtain lead releases from several years for a particular company or group of companies. Expert opinion could be used to determine whether the year-to-year change is reasonable. An expert could determine that the change in releases is out of proportion based on known production processes and emission controls. This approach could provide an indication of the "precision" of the estimates reported by industry.

For secondary data that require manipulation to develop a value(s) suitable for an LCA, the precision DQI could be used to assess the adequacy of the calculation. The results of a calculation could be measured against the mean, standard deviation and the CV for the data. As indicated above, this information would provide an indication of the variability in the data. If this information is unavailable, a more likely scenario would be to assess the precision of the calculation based on expert opinion. Clearly, if expert opinion is the choice, a different expert should review the calculation than the one who developed it.

4.3.2 Bias

Bias refers to *systematic* error that causes the values of a data set to be consistently higher or lower than the corresponding true parameter values. Bias can be created by a weakness in the data collection methodologies, e.g., improper sampling, uncalibrated measurement equipment, or consistently rounding up values. As indicated in Table 4-2 above, bias can be measured by taking the difference between the average measured value ($\bar{X}$) and the reference value of a standard material (T) (EPA, 1984; EPA, 1985; and EPA, 1991). In the example above, bias is -0.5. An alternative index of bias is the percent bias. In the above example, the percent bias is 1 percent (EPA, 1984).

As with precision, the bias DQI can be applied to certain LCA data. This DQI is most applicable to an analysis of measurement devices used to collect primary LCA data. Bias can be used to determine whether the measurement device, as compared against a reference value, exhibits systematic error, i.e., the measured values are consistently higher or lower than the reference values. The bias DQI could also be applied to data generated through modeling. For example, if a company chooses to model its air emissions, model bias could be evaluated if there is a reference air-emissions level or concentration to compare the model results against. Similarly, the bias DQI could be applied to statistically based data provided in the published literature if a reference value is either given or known by the analyst.

The bias DQI is more difficult to apply to modeled or non-measured secondary data. If the data are modeled, bias could be evaluated in one of two ways. The model could be assessed against a standard value to determine if the results are consistently higher or lower than the standard; or expert judgment could be used to make the determination. However, reference materials are not likely to be available to assess the bias in secondary data.

Non-measured secondary data could also be evaluated against the bias DQI. Rather than looking for systematic error in the data, the analyst needs to understand how the data were collected and what the data source actually covers. For example, the TRI database could be used to obtain releases to water for a particular industry. However, facilities that manufacture, produce, or use less than 25,000 pounds of a listed chemical are excluded from the reporting requirements. If the TRI data are used without acknowledging this fact, the LCA would contain an undercoverage bias.

The bias DQI also can be used to evaluate assumptions and calculations used to manipulate LCA data. Again, either expert judgment can be used to assess whether an assumption is biased, or the output of a calculation can be assessed against a reference value.

4.3.3 Accuracy

Accuracy is the degree of agreement between an observed value and an accepted reference value. It includes the cumulative effect of bias (systematic error) and precision (random error). Because precision and bias make up accuracy, it is recommended that the components of accuracy be evaluated separately (EPA, 1985; EPA, 1990; and EPA, 1991). There are four combinations of precision and bias (see Figure 4-2): (a) unbiased and precise; (b) biased and precise; (c) unbiased and imprecise; and (d) biased and imprecise. A data source that is unbiased and precise is highly accurate. The remaining categories represent different levels of inaccuracy.

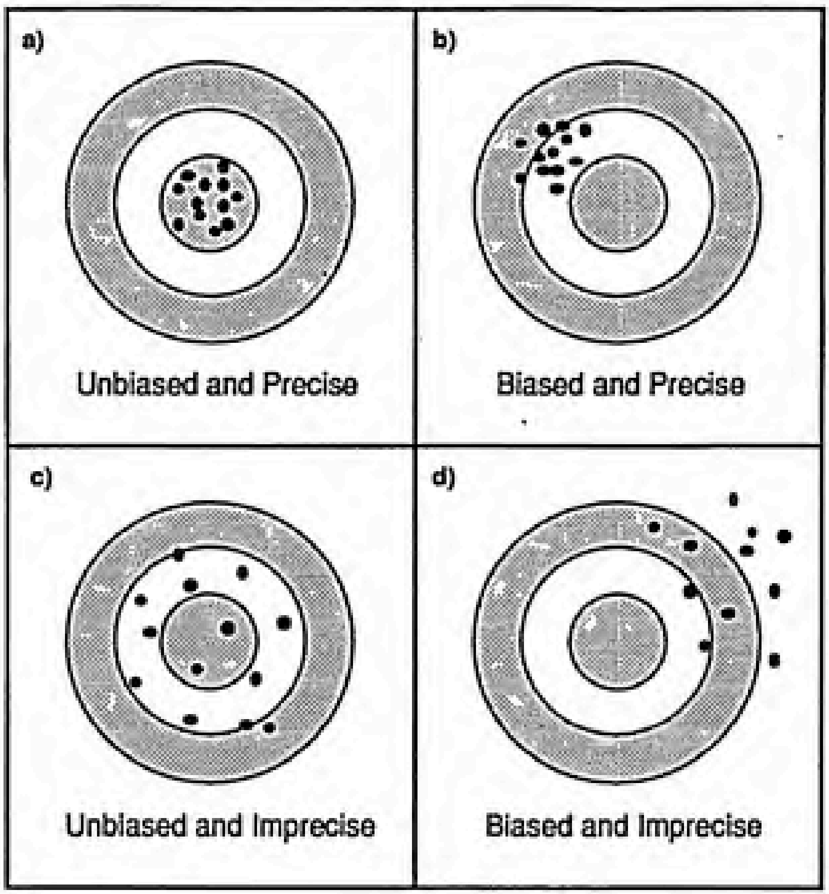


Figure 4-2. Four Combinations of Precision and Bias

4.3.4 Completeness

Completeness refers to the amount of data obtained compared to the amount of data needed. This indicator routinely is expressed as the percentage of obtained data to needed data (Mickler and Medlarz, 1987; EPA, 1990; and EPA, 1991). The operative phrase in this definition is "the amount of data needed." Completeness is largely determined by the goal of the study or data collection effort.

The completeness DQI can be applied uniformly to each form of data likely to be used in an LCA. If the data are statistically based, modeled, or nonmeasured, the completeness DQI can be used to evaluate whether the information, or measurement procedures, provide all the data values necessary. In other words, this DQI could be used to identify if there are missing data or data deficiencies. For example, if an LCA needs air emissions data for 10 facilities in an industry, but the information source includes data for only eight facilities, the data source would be considered 80 percent complete.

The completeness DQI can also be used to evaluate any assumptions and calculations used to manipulate secondary data. Secondary data sources may only provide aggregated data, such as total energy consumption by fuel type (e.g., coal, nuclear, or other), which must be interpolated, extrapolated, or back calculated to develop a facility-specific number suitable for an LCA. Although a data source could be determined to be complete, the requisite assumptions employed by the analyst may be incomplete. An analyst also might have adequate assumptions but poor calculations. Thus, when interpolating, extrapolating, or back calculating data, considering the completeness of assumptions and calculations is important. For example, an analyst uses DOE annual energy data to determine the energy consumption for a particular industry. The DOE data represent total domestic consumption for different energy sources, such as coal-based electricity. The analyst must back calculate the data to determine the energy used by the facility under evaluation. If an assumption is that the facility's energy comes from the closest utility, but further evaluation of the actual energy grid indicates that the energy actually comes from a utility outside the state, incorrect estimates of the source of energy consumed could result. The problem here was that the assumption did not include a specific understanding of energy usage. Incomplete, or deficient, assumptions will lead to inaccurate calculations used to derive LCA data values.

4.4 QUALITATIVE DQIs

4.4.1 Representativeness

Representativeness refers to the degree to which the data describe what an analyst is trying to describe (EPA, 1991d; and Mickler and Medlarz, 1987). This DQI can be used in a variety of ways. From a QA/QC perspective, the representativeness DQI is used to determine if the sampling program design accurately depicts what is needed. This DQI is best met by ensuring sampling locations are selected properly and the appropriate number of samples is collected (Barth et al., 1989).

With respect to LCA data, the representativeness DQI can be used to determine the degree to which primary data represent, or depict, the parameter of interest. For example, if primary air emissions data are collected (or used in the LCA), the representativeness DQI can be used to determine the degree to which the data represent what is being measured, such as peak or average air emissions.

The representativeness DQI can also be applied to secondary data—modeled, measured, or non-measured data. For example, if an LCA required hazardous waste release data for a specific waste stream, the TRI database—a non-measured data source—could be searched to determine if it contains the data for the industry of interest. If the TRI database contained the hazardous waste release data, the data source would be considered representative. This same logic can be applied to secondary data that are modeled or statistically based.

Understanding the distinction between the representativeness and completeness DQIs is important. Continuing with the TRI example, if the database contains the type of hazardous waste releases generated by the selected industry, the data source would be considered representative. However, it is possible that the database would not contain information for all of the facilities studied. In this case, the data source would be representative but not complete.

Applying the representativeness DQI to assumptions and calculations is possible but less important than for the completeness DQI. Data derived through a back calculation may be representative of what the analyst wants to obtain. However, if an analyst's assumptions are incomplete, no matter how representative the data are they still may not reflect the actual value needed in an LCA. In the example given under the completeness DQI for an extrapolated energy value, if an analyst assumes that a facility uses coal-based electricity when, in fact, it uses nuclear-based electricity, the data derived could represent what was perceived to be needed for the LCA: coal-based electricity data values. However, because the analyst's assumption was incorrect regarding the use of nuclear fuel, the data would not reflect the actual value needed in the LCA.

If an analyst's assumptions are evaluated against this DQI, evaluating any subsequent calculations against the representativeness DQI is unnecessary. If an analyst's assumptions are deemed nonrepresentative, then any subsequent calculations also would be nonrepresentative.

4.4.2 Comparability

Comparability is the degree to which different methods, data sets, or decisions agree or can be represented as similar or equivalent (EPA, 1991d). Under the auspices of a QA/QC program, sample data should be comparable with other measurement data for similar samples. More specifically, samples should be collected in a comparable manner, from comparable media and by comparable methods. This is achieved by using standard data collection and analytical techniques (EPA, 1991d; EPA, 1990a).

The comparability DQI is applicable to LCA data. If primary data are used and a QA/QC protocol is followed, the relevance of this DQI is as stated in the previous paragraph. A more complicated matter is the fact that most LCA practitioners also must rely on secondary data sources. For a particular LCA parameter, an analyst could combine more than one data source. Under this situation, it is important that the data sources be comparable. For example, the TRI database contains air, water, and waste release data for industries in SIC code 20 through 39 that manufacture, produce, or use greater than 25,000 pounds of any of 300 listed chemicals. Due to the reporting threshold, the TRI database might not contain certain facility emissions needed in an LCA. If this is the case, an analyst may need to combine the TRI data with other data sources to adequately reflect industry air, water, and waste emissions. If data sources are combined for use in an LCA, it is important that they be comparable. For example, the emissions data should be for the same time frame, reported in or converted to similar units, and of the same type (e.g., industry average) and form (e.g., modeled). The LCA should discuss how these criteria are satisfied so the variation between the data sources is clear to users of the material.

4.4.3 QA/QC

QA/QC is the acronym for quality assurance/quality control, a data quality assessment procedure used to ensure the generation of credible primary data. EPA has developed a QA/QC methodology that is used by each program office when the sampling and analysis of environmental data are undertaken (Barth et al., 1989; NRC, 1988; EPA, 1989; Mickler and Medlarz, 1987; and Neptune et al., 1990). If a primary data source is compiled pursuant to EPA's QA/QC protocol, appropriate information should be available to do a data quality evaluation.

The QA/QC protocol requires that certain objectives or goals be set, that DQIs (such as precision, bias, and representativeness) be used to evaluate the objectives, and that the data are collected pursuant to sound statistical procedures. Accordingly, the QA/QC DQI is applicable to primary data collected through sampling and analysis where the data were generated pursuant to a statistical protocol.

4.4.4 Acceptability

Acceptability refers to whether the data source has been peer reviewed and found to be of good quality, or whether colleagues in the field generally agree that the source is of adequate quality. A secondary data source may not be officially validated or verified (see definitions below), but it could be regarded by colleagues in the field as a data source that contains fairly accurate data. For example, although the TRI database has not been validated or verified, it is an accepted source of air, water, and waste emissions data for those industries subject to the reporting requirements. For an LCA, using the TRI database would be more acceptable than using a database that has not, at a minimum, received similar approval.

The acceptability DQI can also be applied to assumptions and calculations used to interpolate, extrapolate, or back calculate data suitable for an LCA. This DQI, which amounts to a peer review, would require that colleagues in the field determine if the assumptions and calculations used in an LCA are acceptable.

4.4.5 Verification/Validation

Verification and validation refers to whether a data source has been checked for errors and/or evaluated against an accepted method or standard to determine the accuracy of the results. This DQI typically is used to evaluate the quality of models and, subsequently, the modeled data produced as output.

Verification refers to whether the model has been checked to determine if it represents what it is supposed to represent, e.g., emissions from a facility's high-density polyethylene production line. Validation establishes the level of precision and bias in the model results or, in other words, whether the values obtained from the model make sense given what is being modeled. An "acceptable" model should be both verified and validated. If a model is validated but not verified, or verified but not validated, the accuracy of the results could be questioned. A model can be validated by consulting an expert familiar with the process or product being modeled. Model verification involves comparing the model output with actual facility data or a reference value. If the model output equals the known value(s) then the model is likely to generate relatively accurate results (Lewis and Orav, 1989).

The verification/validation DQI is most easily applied to primary data generated through the use of a model. As discussed above, a variety of techniques can be used to ensure the accuracy of the model results. The applicability of this DQI is less clear for modeled secondary data. Unless the model and appropriate documentation can be obtained, only qualitative verification/validation techniques can be employed. Expert judgment could be used to determine if the model results are representative of the industry or facility under evaluation. Similarly, the model output could be compared against known facility input/output values. It is important to note that using expert judgment to validate modeled secondary data causes overlap between the validation/verification and precision DQIs. Expert judgment can be used both to validate model results and determine the natural variability in the model.

4.5 ADDITIONAL DQIs

There are 9 additional DQIs that are useful for assessing the quality of LCA data. These DQIs are particularly directed at the assessment of secondary data sources and involve determining whether the source includes:

- a description of the data collection method,
- a discussion of the limitations in the data collection method,
- statistical measures that are provided or computable,
- model documentation,
- a discussion of the limitations in the model, and
- aggregated or disaggregated data.

Three additional DQIs are relevant when reviewing an existing or published LCA. These include determining whether the data source is:

- accessible,
- reproducible, and
- referenced.

4.5.1 Description of the Data Collection Method

This DQI applies to secondary data that are statistically based or nonmeasured. In both cases, a description of the data collection method would provide additional information to help an analyst assess data quality. With regard to statistically generated data, data quality could be more easily assessed if detail was provided about the sampling procedure used to obtain the data. This sort of information could include:

- a description of the sampling plan,
- a discussion of how the sample was developed,
- an identification of exactly what was measured, and
- an identification of the instruments used to collect the samples.

If the data were generated through the use of a survey, the data source could provide the list of questions. Reviewing the questionnaire could help the analyst determine whether the data reflect the questions asked and whether the data are suitable for the LCA. Without this kind of information determining the accuracy, or overall quality, of the data source would be difficult, if not impossible.

With respect to a non-measured data source, it is equally important from a data quality perspective that the source contain a discussion of why and how the data were collected. For example, the source could indicate whether the data were gathered to fulfill a legal reporting requirement generated by using proxies or generated by using expert opinion. If the data were generated due to a legal reporting requirement, the law could be assessed to determine the extent of coverage. Depending on the LCA, the data may be totally or partially suitable for the analysis. Determining that the data are, among other things, nonrepresentative or contain an undercoverage bias could reduce the usefulness of the database. For data generated with proxies, knowing the basis for the proxy, or how close the comparison is, would provide a good indication of whether the estimates are biased. Similarly, if the data were based on expert opinion, knowing the assumptions and calculations used to generate the data would be helpful.

4.5.2 Enumeration of Limitations in Data Collection Methods

This DQI also applies to secondary data that are statistically based or nonmeasured. A discussion of limitations would provide an indication of the variability (or precision) in the data set. With respect to statistical data, the data source could identify the precision of the measurement instruments and the completeness of the data set (the number of samples collected versus the number needed). If a survey was employed, the data source could indicate, among other things, coverage of the sampling source and the level or degree of nonresponse. With a statistical sample or a survey, the source could discuss whether there were missing values, or data deficiencies, and if these problems were compensated for.

With regard to non-measured data, the data source also could discuss the sources of variation in the data set. This could include a discussion of data deficiencies (e.g., companies who were required to report but reported the data incorrectly) as well as limitations in any proxies used, or lack of procedures to check that data were properly input to the database or spreadsheets.

4.5.3 Provision of Statistical Measures

Statistical measures, such as the mean, standard deviation, and skewness, are quantitative measures that can be used to determine the central tendency and variability in a data set. The mean (or average) provides an indication of the central tendency in the data. The standard deviation indicates how the data are dispersed about the mean; and skewness demonstrates how symmetrical the data are, or in which direction the data are most heavily drawn. With regard to skewness, if the statistic is positive, the distribution is positively skewed; if the statistic is negative, the distribution is negatively skewed; and if the statistic is zero, the distribution is symmetrical. From the standpoint of data quality, it would be beneficial if a data source either provided these measures or enabled their calculation. The standard deviation would provide an indication of the variability in the data, the mean would indicate the center of the data, and skewness would indicate if the distribution is being pulled (in one direction or another) by a subset of the facilities or industries studied.

Primary data generated through sampling or modeling can be used to calculate these statistical measures. Relying on secondary data sources, however, means that the source must either provide the statistical measures or have the data in a format (e.g., nonaggregated) that permits their calculation.

4.5.4 Provision of Model Documentation

Knowing whether a model is documented is particularly important for secondary data. In using a secondary source that contains modeled data, the analyst could use the documentation to verify the model outputs, perform sensitivity analyses, and check the assumptions, calculations, and algorithms employed in the model. Documentation for primary data that are modeled is equally important. In some cases, facilities will develop models for the facility-specific data, but in other cases, they will use "off-the-shelf" models. In the former case, the developer of a model should ensure that it is validated and verified. In the latter case, however, having access to the model documentation is as important as it is for a secondary data source.

4.5.5 Enumeration of Model Limitations

Secondary data sources generated through the use of models should both provide the model documentation and identify any limitations associated with the model. Determining a model's limitations helps clarify the uncertainty associated with the model. A discussion of model limitations would include, among other things, any simplifying assumptions used in the model, whether variables were dropped from consideration, and the relationship between the dropped variables and those used in the model.

4.5.6 Level of Data Aggregation

Data aggregation is used as a separate DQI from statistical measures provided or computable due to the amount of additional information that can be obtained from non-aggregated data. A data source that contains aggregated data is perceived as having lower data quality. This disadvantage can, however, be overcome if the data source provides statistical measures or a description of the variability and overall limitations associated with the data. Non-aggregated data, on the other hand, can be used to calculate statistical measures, and for a variety of other purposes. These data can be assessed to determine trends or relationships in the data and the variation between facilities or industries. Non-aggregated data also are likely to be more amenable to phases two and three of an LCA (i.e., impact analysis and improvement analysis), which may need individual facility data to both determine environmental and human health impacts and identify steps necessary to improve facility-related problems.

4.5.7 Accessibility

Accessibility refers to whether a data source can be easily obtained. If an LCA does not adequately discuss the quality of the data sources used in the analysis, going back to the original data sources to evaluate the data quality may be necessary. In some cases, data used in LCAs may be proprietary and, therefore, inaccessible to an outside reviewer. In other cases, data sources used in an LCA could be unretrievable. For example, a federal database could be revised and superseded by another database, such that access to the old database is not possible. Under both scenarios, a reviewer would be unable to obtain the data source to assess its quality.

4.5.8 Reproducibility

A thorough data quality evaluation may warrant trying to reproduce portions, or all, of an LCA. Reproducing an analysis is one way of ensuring that it is credible. To be reproducible, the LCA must be transparent enough that a different analyst can understand the data, calculations, assumptions, and models used.

4.5.9 Level of Reference

To adequately review the quality of a data source used in an LCA, an analyst must have a complete reference for the source. If the LCA itself does not include a data quality section, the authors should clearly indicate what data sources were used, who developed the sources, and when they were published. An adequate reference enables an analyst to go directly to the source to gain a better understanding of its quality and how it was used in the LCA.

CHAPTER 5
DATA QUALITY ASSESSMENT FRAMEWORK FOR LIFE CYCLE ASSESSMENTS

This chapter provides a framework for assessing the quality of LCA data. LCA data quality is influenced by three factors, data sources, and any assumptions and calculations used to generate LCA data values. The framework uses a scoring system to evaluate each factor that influences LCA data quality against a recommended set of DQIs, it provides a system of worksheets for tallying this information into a usable format, and finally a matrix is used to identify the data quality associated with all (or the most important) input/output streams for each stage of a life cycle inventory. Provided below is a detailed discussion of the three components that comprise the LCA data quality assessment framework.

5.1 DQI HIERARCHY AND SCORING SYSTEM

The DQI hierarchy and scoring system combines the concepts of decision analysis (Clemen, 1991) and the Data Reliability Indicator (DRI) system developed by Kollig (1987) (see Appendix C). The system is be used to calculate normalized data quality scores (DQS) for each, or the most important, LCA parameters, where each score ranges between 0 and 1. For each parameter there will be one or three scores: one score if only the data source is evaluated and, at most, three scores if the data source, assumptions, and calculations are evaluated. A number closer to one indicates that the data are of higher quality whereas a number closer to 0 indicates that the data are of lower quality.

The scoring system is based on assigning weights between 0 and 5 to each DQI in the system. A 5 is the highest weight, or indication of the importance to data quality, and a 0 is the lowest weight. The assignment of weights to each DQI is based on the importance of the indicator to the assessment of data quality. This approach is subjective; practitioners must use their judgment as to the relative importance of each DQI. For example, the practitioner must decide whether primary data should be valued more highly than secondary data and which DQIs should carry the highest values.

Figures 5-1 and 5-2 present the DQI hierarchy and the scoring system. Figure 5-1 can be used to assess the quality of an LCA data source, and Figure 5-2 can be used to assess the quality of assumptions and calculations employed if the analyst must calculate numbers to arrive at a value suitable for an LCA. LCAs that use a different combination of weights should describe any restructuring of the recommended weighting system.

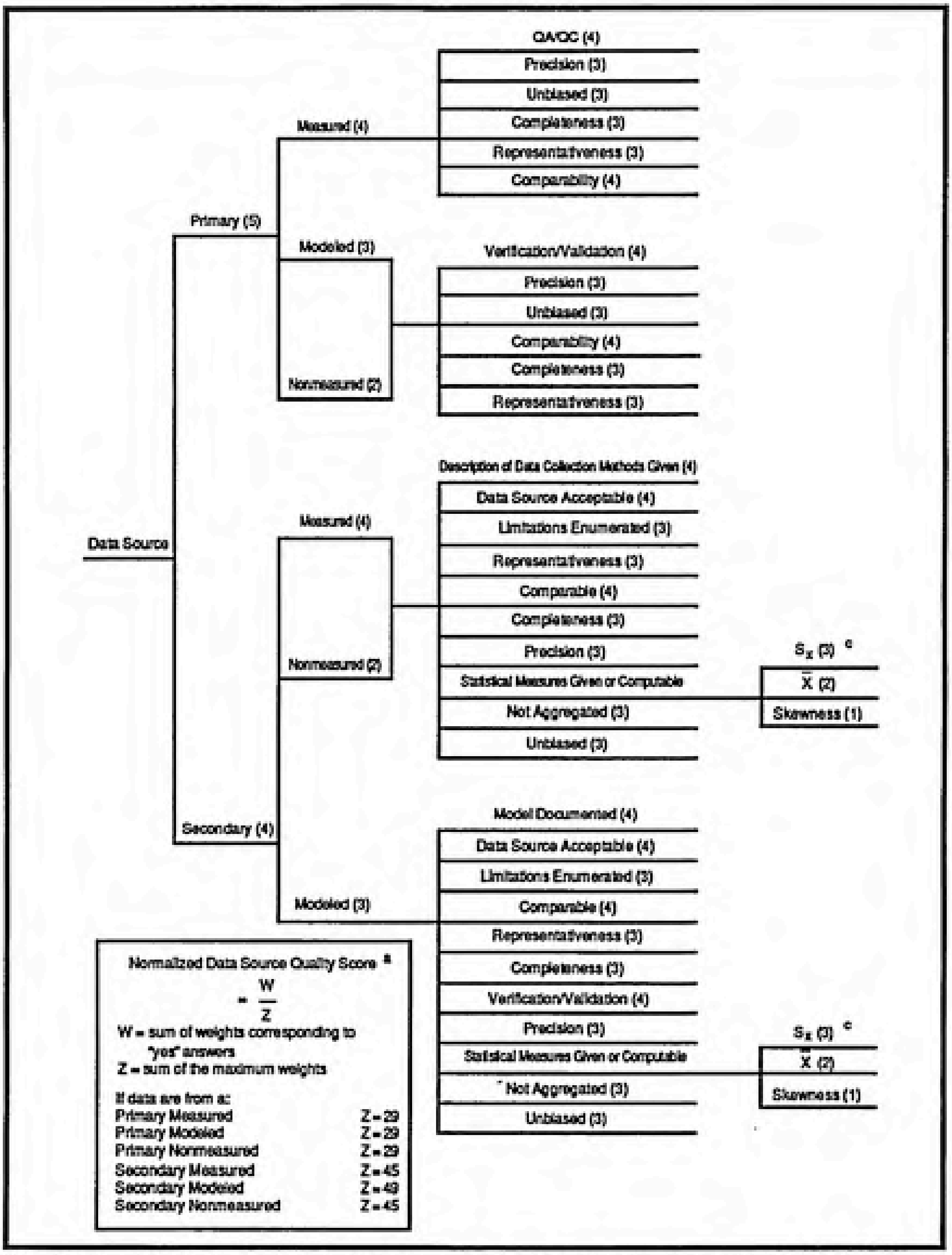
The hierarchy presented in Figures 5-1 and 5-2 are to be used by analysts or practitioners conducting an LCA. If an analyst wants to review the data quality of an existing LCA, the following DQIs should be added to each branch of both trees: accessibility, reproducibility, and referenced.

The DQI hierarchy and scoring system provides a framework, or thought process, for evaluating the quality of data used in LCAs. Practitioners typically use dozens of data sources to obtain information/data for use in LCAs. It is not recommended that practitioners apply the framework to every data source (or assumption and calculation) that is used or evaluated for use in an LCA. Rather, based on the judgment of practitioners, the framework should be applied to the key data sources (or assumptions and calculations) used to generate data for each - or the most important - stages of a life cycle inventory.

Scoring systems such as this one have been met with mixed responses (Clemen, 1991; Kollig, 1987; and Funtowicz and Ravetz, 1986). These type of systems use subjectively assigned numbers rather than values derived from observations or models. . In this context, the scores can be influenced by the weights assigned to the different DQIs. The approach outlined below, however, offers two primary benefits. First, it provides a detailed framework for evaluating LCA data quality. Second, if an LCA practitioner applies the framework, and documents why different weights were selected, users of the material will have a basis for evaluating the judgments made about LCA data quality. Thus, the system provides a framework for displaying in a transparent and structured manner the quality associated with LCA data values.

5.2 DQI SCORING SYSTEM

Figures 5-1 and 5-2 provide the DQI hierarchy and scoring system. As indicated, the system is based on whether the data evaluated are primary or secondary, and on the form of the data, i.e., measured (statistical or nonstatistical), nonmeasured, or modeled. Weights between 0 and 5 are assigned to each of these categories, and to each applicable DQI. The assignment of the weights is a subjective process, but should be based on the relative importance of each data category and DQI to an evaluation of data quality.

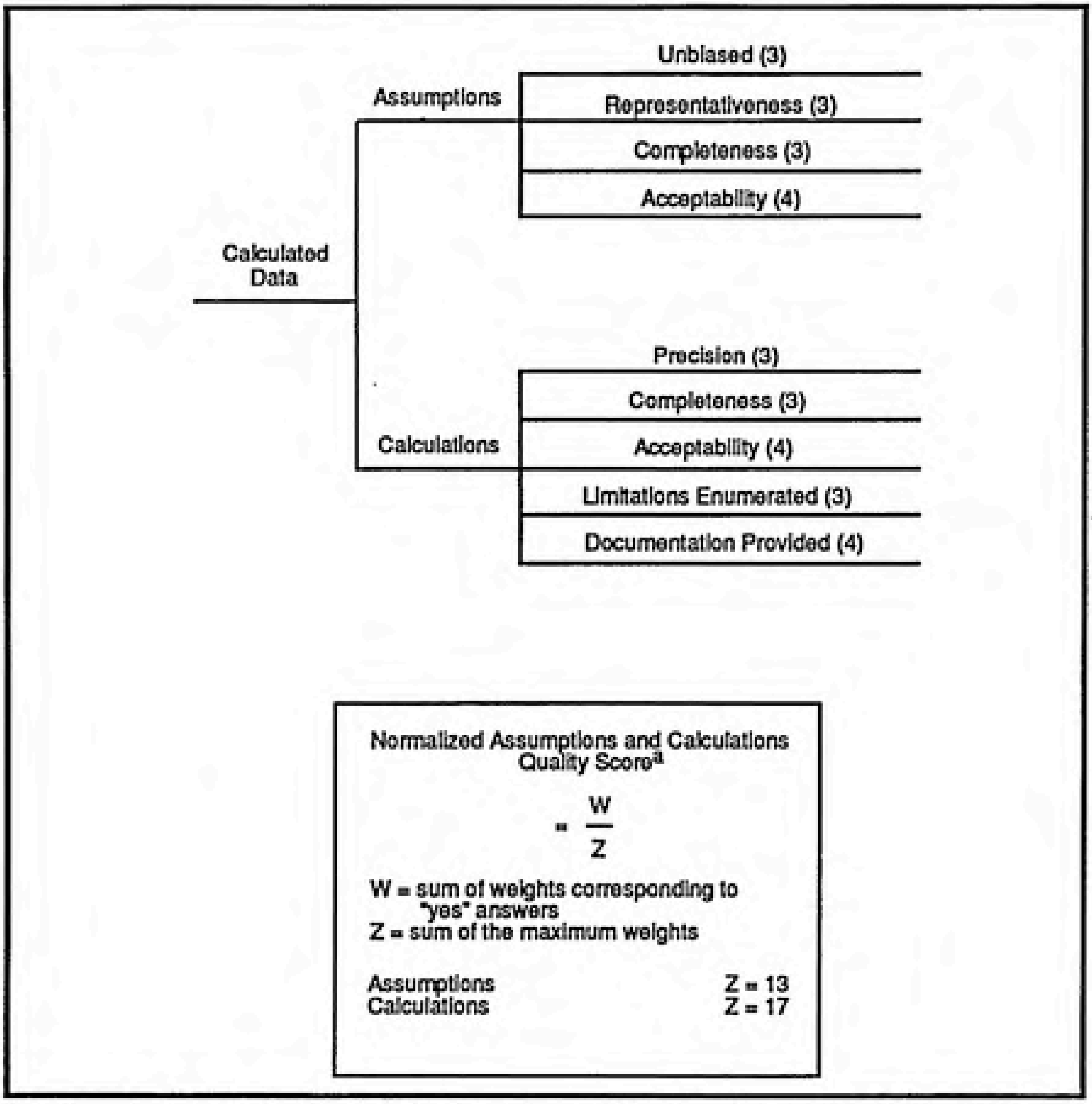


[a]The denominator is calculated by summing the maximum weights for each category or subcategory, and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

[b]There can be only one answer to the age DQI. Thus, "5" (the maximum weight) should be used in the denominator.

[c]There can be a "yes" answer to each of these criteria. Thus, the contribution to the denominator is "6".

Figure 5-1. Hierarchy for Assessing the Quality of LCA Data Sources



[a]The denominator is calculated by summing the maximum weights for each category or subcategory and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

Figure 5-2. Hierarchy for Assessing the Quality of Calculated LCA Data

The remainder of this section explains how the data quality framework should be scored. The scores are based on the subjective assignment and the relative importance of each data category and DQI. Practitioners can modify the list of DQIs as well as the associated weights. However, any modifications to the system should be explained in a data quality section or an appendix to the LCA.

5.2.1 Explanation of Scoring System

Figure 5-1 allows an analyst to calculate a normalized "data source quality score." The first breakdown in the category is based on whether the data are primary or secondary. Primary data, which are facility-specific in nature, have been assigned a weight of (5) whereas secondary data, which have less certain quality, have been assigned a weight of (4). Primary data are broken down further based on whether the data are measured, modeled, or nonmeasured. A higher weight has been assigned to sampled data (4) than modeled data (3) or nonmeasured data (2) due to the fact that the latter two have the potential for greater variability, or uncertainty.

Secondary data also are broken down into subcategories. These subcategories and their assigned weights are measured data (4), modeled data (3), and nonmeasured data (2).

The analyst must ask a series of questions about each subcategory of primary and secondary data. The questions, or DQIs, and their associated weights, are as follows:

- Was a QA/QC protocol followed? (4)
- Are the data precise? (3)
- Are the data unbiased? (3)
- Are the data (or is the data source) complete? (3)
- Are the data (or is the data source) representative? (3)
- Are the data (or is the data source) comparable? (4)
- Has the model been validated/verified? (4)
- Is a description of the data collection method given? (4)
- Are the limitations of the data collection methods given? (3)
- Is the data source widely accepted? (4)
- Is the model documentation provided? (4)
- Are the model limitations enumerated? (3)
- Are the data not aggregated? (3)
- Are statistical measures given or computable? (This is broken down by three different measures: the standard deviation (3), the mean (2), and skewness (1). (Because there could be a "yes" answer for each of these measures, the total weight is (6).) (6)

Figure 5-2 allows the analyst to calculate normalized "assumption and calculation data quality scores." These categories are relevant when a practitioner manipulates data for use in an LCA. Sufficient uncertainty is associated with the assumption and calculation categories such that weights have been assigned to the DQIs only.

5.2.2 Calculating the Data Quality Score

The data quality scores are determined by summing the weights associated with each "yes" answer to the DQIs and dividing this number (the numerator) by the sum of the maximum weights for each category and subcategory (the denominator). For example, the sum of the maximum weights for modeled secondary data is 45. This is obtained by adding (5) for primary data, the maximum weight for the category, (4) for statistically sampled or census data, the maximum weight for the subcategory, and the numbers identified next to each DQI for modeled data, which are as follows: model documented (4), data source acceptable (4), limitations enumerated (3), representativeness (3), completeness (3), validated/verified (4), precision (3), not aggregated (3), unbiased (3), and statistical measures given or computable (6). Next, all of the "yes" answers for the modeled data source DQIs are totaled and divided by 45.

If a DQI is not applicable to the data source (or assumptions and calculations) under evaluation, it should be removed from the denominator. If it is not removed, the denominator would be larger than necessary, and the score would be biased downwards.

5.3 RELATIONSHIP BETWEEN THE DATA QUALITY SCORE AND DQGS

The data quality score (DQS) for data sources, assumptions or calculations should be compared against the previously identified DQGs. There is not, however, a direct correspondence between the DQS and the DQGs. For example, a DQG with a 90 percent confidence limit does not mean that a DQS must be 1.0 to be considered acceptable. Rather, DQGs are meant to serve as internal accounting mechanisms. Once a DQS has been assigned to a data source (assumption or calculation), it should be related to the appropriate DQG to ensure that the goals of the analysis have been met. Due to the subjective nature of the scoring system, it will be up to the analyst to determine the DQS (e.g., 0.65 or 0.95) that constitutes achievement of an associated DQG.

5.4 DATA QUALITY WORKSHEETS

After selecting the weights for the DQI hierarchy and evaluating the data against applicable DQIs, the analyst can document the weights in a data quality worksheet. Tables 5-1 and 5-2 provide worksheets for LCA data sources, assumptions, and calculations, respectively. The number of "yes" answers can be totaled from the worksheet and used as the numerator of the normalized score. The denominator should represent the maximum weight assigned to each DQI. As indicated above, if a DQI is not applicable, remove its score from the denominator. Also, the analyst should calculate one score for each data source assessed and two separate scores if assumptions and calculations are also evaluated. For each data source, an analyst could use between one and three worksheets. Practitioners should consider providing copies of the key or appropriate data quality worksheets in an appendix to the LCA.

5.5 DATA QUALITY MATRIX

Figure 5-3 provides an LCA data quality matrix which can be used by practitioners to summarize the data quality information for each LCA parameter, or the most important parameters. The matrix lists the LCA inputs and outputs horizontally, and the stages of a life cycle vertically. Based on the data quality score, the cells should be filled in with proportional shading, between 0 and 100 percent, which indicates the level of data quality achieved. If multiple data sources are evaluated per cell, the cell should contain multiple circles. (It is not recommended that the data quality scores be averaged because averaging the numbers would erode the power of the scoring system.) An "N/A" should be used to designate those cells not applicable to the particular LCA. See Figure 5-3 for an example data quality matrix.

The matrix provides a visual representation of the data quality achieved for each parameter of the LCA. Practitioners could include the matrix in an LCA data quality section and provide the relevant and appropriate report cards in an appendix.

5.6 JUSTIFICATION FOR USING THE FRAMEWORK

The framework outlined above presents a rational and consistent methodology for analyzing and reporting the quality of data used in LCAs. However, given the breadth and subjective nature of the system, practitioners may view the process as time consuming and burdensome. Yet, if the system is used as proposed, the following benefits would result:

LCA data sources would be evaluated against the same criteria; therefore, a consistent data quality comparison could be made between LCA data sources,

the scoring system would provide practitioners with increased confidence to accept or reject LCA data sources, and increased confidence in LCA results, reporting the weights would provide users of the material with an indication of the relative importance assigned to each DQI by the practitioner, and

reporting the quality associated with LCA data sources and values would increase the transparency of LCA results to users of the material.

The framework, including the scoring system, worksheets, and matrix, could be viewed as the "gold standard" of data quality evaluation systems. It is a recommended, and thorough, approach to deriving and reporting LCA data quality. It is not, however, the sole means for identifying and defining data quality concerns. For example, practitioners could use the tree hierarchy, without the weights, to determine which DQIs could be applied to different types of data sources and assign an overall data quality ranking of high/medium/low.

A system based on a high/medium/low ranking may not provide a completely consistent assessment process, however. Unless there are criteria defining what constitutes high, medium and low, data quality rankings may not be identified consistently across different data sources. The "gold standard" approach, however, recommends that practitioners make judgments about the relative importance of each DQI and then hold each data source to the same evaluation standard. In short, even though the framework includes a subjective component, the assignment of weights and the calculation of a score, it provides a rational methodology for conducting consistent data quality evaluations.

TABLE 5-1. DATA QUALITY WORKSHEET: LCA DATA SOURCES

Name of Data Source: ____________________

Data Form/DQI	Yes	No	N/A	DQ Weight
Primary				
Secondary				
Measured				
Modeled				
Nonmeasured				
QA/QC				
Precision				
Bias				
Comparable				
Completeness				
Representativeness				
Verification/Validation				
Description of Data Collection Methods				
Acceptability				
Provision of Data Limitations				
Statistical Measures				
Level of Aggregation				
Model Documentation				
Model Limitations				
Total Score				

[a]The denominator is calculated by summing the maximum weights for each category or subcategory and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

Legend:

Normalized Data Source Quality Score[a]

$$= \frac{W}{Z}$$

W = sum of weights corresponding to "yes" answers
Z = sum of the maximum weights

If data are from a:

Primary Measured	Z = 29
Primary Modeled	Z = 29
Primary Nonmeasured	Z = 29
Secondary Measured	Z = 45
Secondary Model	Z = 49
Secondary Nonmeasured	Z = 45

TABLE 5-2. DATA QUALITY WORKSHEET: ASSUMPTIONS AND CALCULATIONS

Assumption: ______________________________

Calculation: ______________________________

DQI	Yes	No	N/A	DQ Weight
Representativeness				
Completeness				
Verification/Validation				
Documentation Provided				
Precision				
Bias				
Acceptable				
Provision of Data Limitations				
Total Score				

[a] The denominator is calculated by summing the maximum weights for each category or subcategory and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

Legend:

Normalized Assumptions and Calculations Quality Score[a]

$$= \frac{W}{Z}$$

W = sum of weights corresponding to "yes" answers

Z = sum of the maximum weights

Assumptions $Z = 13$

Calculations $Z = 17$

TABLE 5-3 EXAMPLE LCA DATA QUALITY MATRIX

Inputs/ Outputs Life Cycle Stages	Energy Use	Raw Materials Use	Air Releases	Water Releases	Waste Releases	Co-Products
Raw Materials Aquisition	◔	◕	N/A	◔	◑	N/A
Manufacturing	◕	●	◕	◕	◔	◑
Use/Reuse/ Maintenance	◕	N/A	◕	◔	◑	N/A
Recycle/ Waste Management	◑	N/A	N/A	◑	◑	N/A

Provided below is an application of the data quality framework.

5.7 DATA QUALITY FRAMEWORK: EXAMPLE

A practitioner conducts an external LCA on the production of rayon to determine the impacts from using the primary raw material, carbon disulfide. Three companies produce rayon domestically: Courtaulds Fibers, Incorporated, North American Rayon, and Lenzing Corporation. The practitioner is not one of the companies, therefore, only secondary data sources are available for use in the LCA. Three data sources are used to determine the air emissions, raw materials use, and energy use during the manufacturing stage of the life cycle inventory; EPA's *Toxic Release Inventory*, EPA's *AP-42 Emission Factors for the Synthetic Fiber Industry*, and DOE's *Annual Energy Outlook (EPA 1990c; PES, 1989; EIA, 1992a)*.

Air emissions for each facility can be obtained directly from the TRI database. Raw materials use is determined by multiplying the AP-42 emission factor for the use of carbon disulfide (500 lbs/ton of rayon fiber produced) by the total quantity of rayon fiber produced by each facility. Finally, based on the type of energy used by each facility, total energy use figures are back-calculated from the aggregate industry data provided in DOE's *Annual Energy Outlook*.

The following pages include the report cards and associated data quality scores for each of the above-listed data sources. An example data quality matrix also is provided.

RAYON EXAMPLE
DATA QUALITY WORKSHEET #1

Name of Data Source: TRI Database

Data Form/DQI	Yes	No	N/A	DQ Weight
Primary		●		
Secondary	●			4
Measured		●		
Modeled		●		
Nonmeasured	●			2
QA/QC		●		
Precision		●		
Bias		●		
Comparable	●			4
Completeness	●			3
Representativeness	●			3
Verification/Validation				
Description of Data Collection Methods	●			4
Acceptability	●			4
Provision of Data Limitations		●		
Statistical Measures	●			6
Level of Aggregation	●			3
Model Documentation		●		
Model Limitations		●		
Total Score			33/45=	.73

[a]The denominator is calculated by summing the maximum weights for each category or subcategory and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

Legend:

Normalized Data Source Quality Score[a]

$$= \frac{W}{Z}$$

W = sum of weights corresponding to "yes" answers
Z = sum of the maximum weights

If data are from a:

Primary Measured	Z = 29
Primary Modeled	Z = 29
Primary Nonmeasured	Z = 29
Secondary Measured	Z = 45
Secondary Model	Z = 49
Secondary Nonmeasured	Z = 45

RAYON EXAMPLE
DATA QUALITY WORKSHEET #2

Name of Data Source: AP-42 Emission Factors

Data Form/DQI	Yes	No	N/A	DQ Weight
Primary		●		
Secondary	●			4
Measured		●		
Modeled	●			3
Nonmeasured		●		
QA/QC		●		
Precision		●		
Bias		●		
Comparable	●			4
Completeness		●		
Representativeness	●			3
Verification/Validation		●		
Description of Data Collection Methods		●		
Acceptability	●			4
Provision of Data Limitations		●		
Statistical Measures			●	
Level of Aggregation		●		
Model Documentation		●		
Model Limitations	●			3
Total Score			21/45=	.46

[a]The denominator is calculated by summing the maximum weights for each category or subcategory and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

Legend:

Normalized Data Source Quality Score[a]

$$= \frac{W}{Z}$$

W = sum of weights corresponding to "yes" answers
Z = sum of the maximum weights

If data are from a:

Primary Measured	Z = 29
Primary Modeled	Z = 29
Primary Nonmeasured	Z = 29
Secondary Measured	Z = 45
Secondary Model	Z = 49
Secondary Nonmeasured	Z = 45

RAYON EXAMPLE
DATA QUALITY WORKSHEET #3

Name of Data Source: Annual Energy Outlook

Data Form/DQI	Yes	No	N/A	DQ Weight
Primary		●		
Secondary	●			
Measured	●			4
Modeled		●		
Nonmeasured		●		
QA/QC		●		
Precision		●		
Bias		●		
Comparable	●			4
Completeness	●			3
Representativeness	●			3
Verification/Validation	●			4
Description of Data Collection Methods	●			4
Acceptability	●			4
Provision of Data Limitations	●			3
Statistical Measures		●		
Level of Aggregation		●		
Model Documentation		●		
Model Limitations		●		
Total Score			29/45=	.64

[a]The denominator is calculated by summing the maximum weights for each category or subcategory and the numerator is calculated by summing the weights associated with each "yes" answer to the applicable DQIs.

Legend:

Normalized Data Source Quality Score[a]

$$= \frac{W}{Z}$$

W = sum of weights corresponding to "yes" answers
Z = sum of the maximum weights

If data are from a:

Primary Measured	Z = 29
Primary Modeled	Z = 29
Primary Nonmeasured	Z = 29
Secondary Measured	Z = 45
Secondary Model	Z = 49
Secondary Nonmeasured	Z = 45

RAYON EXAMPLE
DATA QUALITY MATRIX

Inputs/ Outputs — Life Cycle Stages	Energy Use	Raw Materials Use	Air Releases	Water Releases	Waste Releases	Co-Products
Raw Materials Aquisition						
Manufacturing						
Use/Reuse/ Maintenance						
Recycle/ Waste Management						

CHAPTER 6
APPLICATION OF SENSITIVITY AND UNCERTAINTY ANALYSIS TO LIFE CYCLE ASSESSMENT DATA

Once data have been collected for a life cycle inventory, it is appropriate, where possible, to determine which parameters are most important to LCA results. This type of determination can help identify where additional resources should be directed to improve LCA data quality. For example, finding that small changes in a parameter have significant impacts on LCA outputs would indicate that the parameter is important to the analysis and that high quality data are more critical for that parameter. Determining which model parameters are most sensitive to LCA results does not indicate that data quality is good or bad. Rather, sensitivity and uncertainty analysis techniques can be used to gain an understanding of the significance and uncertainty in model parameters, and direction for the allocation of resources to enhance data quality.

This chapter reviews the utility of sensitivity and uncertainty analysis for evaluating LCA data quality. Sensitivity analysis typically is used to determine the effect of changes in model inputs on model outputs (Morgan and Henrion, 1990; Clemen, 1991). Uncertainty analysis is used to measure (based on probability assignments) the degree to which the uncertainty in each input contributes to the total uncertainty in model outputs (Morgan and Henrion, 1990; Vesely and Rasmuson, 1984; EPA, 1985; and Finkel, 1990).

Three methods for conducting sensitivity analysis (also referred to as deterministic sensitivity analysis) are discussed below. These methods require generating a mathematical model to evaluate the relative importance of system parameters. LCA practitioners typically develop models to determine the effects of process inputs on outputs. These models can also be used to assess the sensitivity of individual, or all, LCA parameters. As discussed more fully below, sensitivity analysis can be performed on all types of LCAs: internal, external, comparative, and noncomparative.

Uncertainty analysis (also referred to as probabilistic sensitivity analysis) may be applicable to LCA data. As indicated, this methodology is used to evaluate the uncertainties in model inputs based on their relative contribution to the total uncertainty in model outputs (Morgan and Henrion, 1990). Uncertainty analysis requires developing probability distributions and applying different mathematical methods-such as error propagation, using first-order, or Gaussian, approximations and Monte Carlo Simulation-to determine all possible combinations of uncertain parameters. Although more complicated mathematically, and requiring more information, than deterministic sensitivity analysis, uncertainty techniques can be used to indicate the level of uncertainty associated with the most important (or sensitive) LCA variables. Parameters that are both sensitive and uncertain are candidates for more focused data quality concerns. Uncertainty techniques may also be used to determine the total uncertainty in final LCA results.

Provided below is a discussion of sensitivity and uncertainty analysis methodologies and their applicability to LCA data quality.

6.1 DETERMINISTIC SENSITIVITY ANALYSIS

Deterministic sensitivity analysis is used to define relevant variables, to characterize their relationship in formal models, and to assign values to possible outcomes (Spetzler and Von Holstein, 1975). In effect, sensitivity analysis is used to determine what does and does not matter in a model. Generally, this is accomplished in a step-wise fashion by varying different model inputs (one at a time while holding all other parameters constant) and assessing the impact on model outputs (Clemen, 1991; Morgan and Henrion, 1990). This technique provides an indication of the relative importance of model parameters, and where additional efforts are needed to improve the quality of the analysis (Buede, 1987). Sensitivity analysis is also used to help decision-makers understand the consequence of different decisions and which options should be preferred over others (Buede, 1987; McNamee and Celona, 1987). Analysts use the following graphic and mathematical techniques to depict model sensitivity: "tornado graphs" (for one-way analyses); two or three-way graphs; and simple ratios that depict the sensitivity between parameters in the same model or in different models (Clemen, 1991; North, 1990). Each of these techniques, and their applicability to LCA data quality, is discussed below.

6.1.1 Tornado Graphs

A common method for determining model sensitivities is to generate a tornado diagram. This diagram, typically provided as a bar graph, indicates the degree to which model outputs vary due to changes in specific inputs (Clemen, 1991). In the diagram, the top bar, which is always the longest, indicates that it is the most sensitive variable, and the bottom bar, which is always the shortest, indicates it is the least sensitive variable (see

Figure 6.1). The graph is created by developing a model of the system or problem under evaluation, and then selecting high and low values for each variable, while holding all other variables constant, to determine the relative impact of individual parameters on the model outputs.

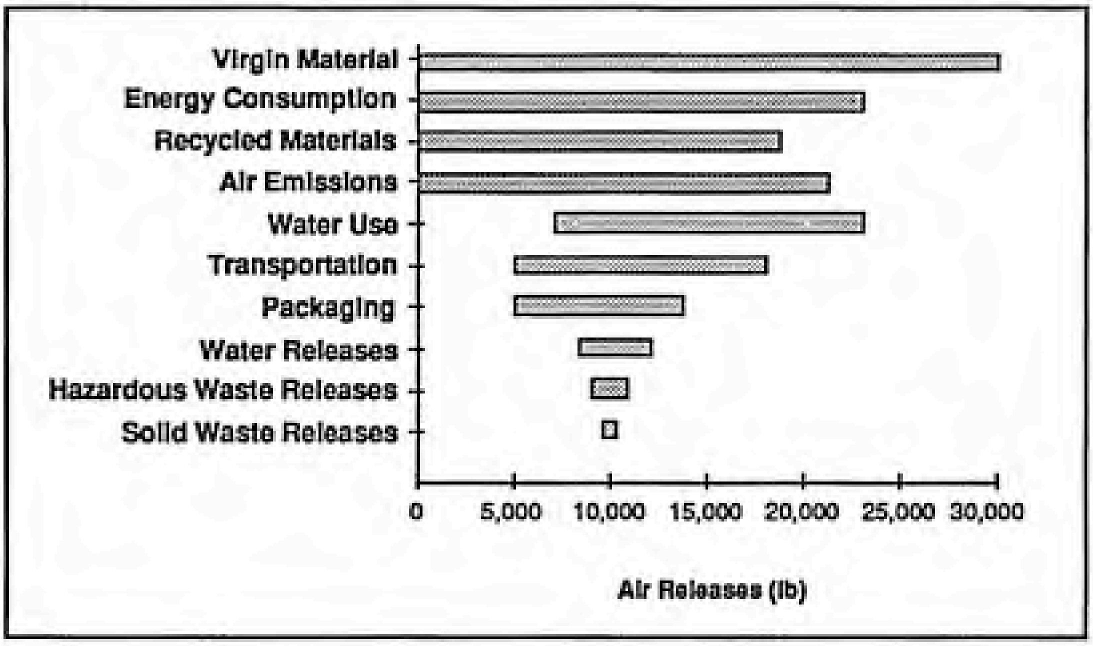


Figure 6-1. Sensitivity of Air Releases for PET Soft Drink Delivery System

This is a relatively simple sensitivity analysis technique that may be amenable to evaluating the relative importance of different LCA parameters. For example, Figure 6-1 presents a hypothetical tornado diagram of air releases from the production of PET soft drink delivery systems. The lengths of the bars represent the extent to which air emissions are sensitive to different LCA parameters, e.g., raw material inputs (both virgin and recycled), energy and water inputs, and various waste stream outputs. In this case, changes in the use of virgin materials have the greatest impact on total air releases. From a data quality perspective, this information demonstrates that, due to the sensitivity in the virgin raw material parameter, particular attention should be paid to the quality of the data used for this variable.

Although the tornado graph is a simple sensitivity analysis technique, it requires the development of a mathematical model to evaluate the relationship between model inputs and outputs. LCA practitioners analyze numerous parameters and information sources when building a life cycle inventory. The pertinent information typically is entered into a computer and a model of the major input/output processes is developed (ADL, 1993). Given that LCA practitioners use models to evaluate LCA results, it is appropriate to perform sensitivity analyses to determine the most sensitive LCA parameters, and to use the results of such analyses to help focus limited data quality resources.

The tornado graph is most applicable to an evaluation of the sensitivity in single models or systems. However, if a comparative LCA is conducted, this approach can be applied to each model independently where the results of each tornado graph could be compared to determine the most sensitive parameters in each system.

6.1.2 Two-Way or Three-Way Sensitivity Analyses

Unlike the tornado diagram, which allows the modification of one variable at a time, a two or three-way sensitivity analysis allows the evaluation of multiple variables simultaneously. Multiple sensitive variables can be evaluated to determine which combination minimizes or maximizes a parameter of interest, e.g., total air emissions. For example, an LCA practitioner may be concerned with the impact of raw materials use and energy consumption on total air emissions. As indicated in Figure 6-2, this two-way sensitivity is represented as a rectangular box that indicates all possible values of each variable. Like tornado graphs, the two-way graph uses base values for all variables except the ones of interest (raw materials use and energy consumption), which are varied between their extreme values to indicate the appropriate break even points (depicted by points A and B). Point A indicates that when energy consumption is 0 Btu, raw materials use is 200 million pounds, and when energy consumption is 400 million Btu, raw materials use is 800 million pounds. The area above and below the line represents the regions where air emissions are greater or less than 100,000 pounds. The point labeled C represents the model results for each parameter calculated at its base value. The point labeled D depicts the level of raw materials use and energy consumption needed to drop air emissions below 100,000 pounds.

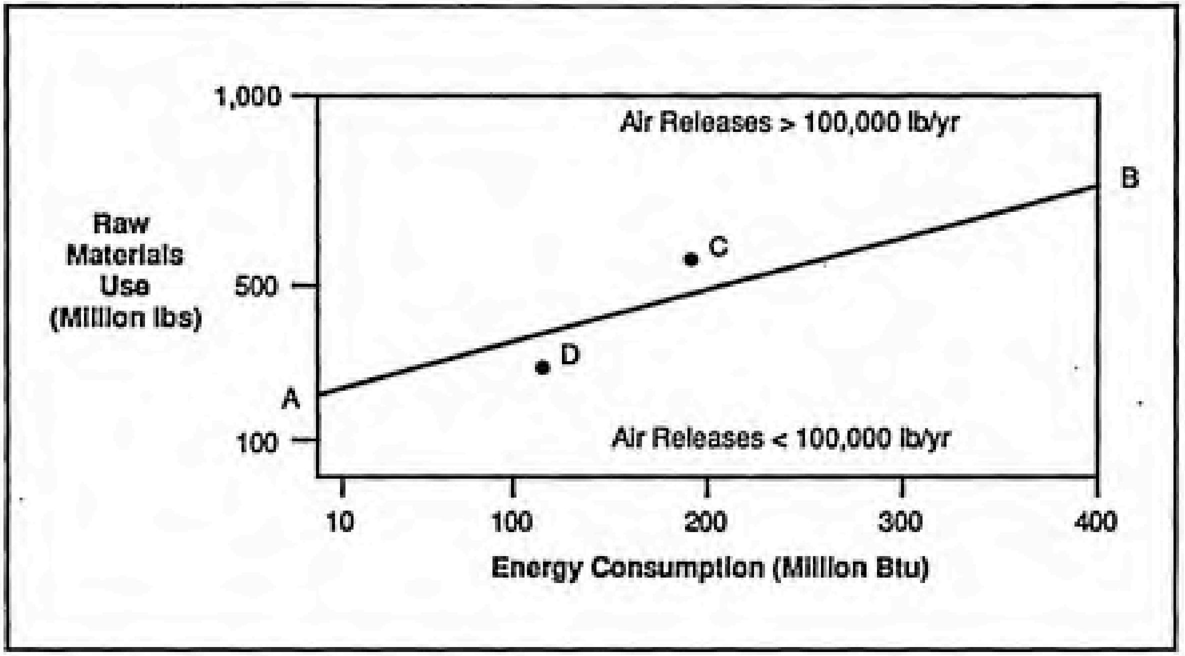


Figure 6-2. Example: Two-Way Sensitivity Graph

This sensitivity analysis technique is best used when evaluating trade offs between parameters or when making judgments or decisions from model results. This technique is more applicable to the second phase of an LCA (impact assessment) than an LCA data quality evaluation. When evaluating LCA data quality, sensitivity analysis is most useful where it highlights the most sensitive parameters to provide an indication of where data quality resources should be focused. This information can be obtained more easily from tornado graphs and simple ratio calculations discussed below.

6.1.3 Ratio Sensitivity Analyses

Sensitivity in model parameters can also be expressed as a ratio (North, 1990; and Morgan and Henrion, 1990). This method typically is applied in comparative analyses, and is applicable to comparative LCAs. Rather than varying inputs one at a time to determine the effect on model outputs, two systems or processes can be compared according to an identified criterion, e.g., total emissions where the process with the lowest emissions is ranked higher. A ratio is calculated to determine the percentage that a parameter would have to change to reverse the rankings. One LCA practitioner refers to this as the "percent error needed to reverse the total ranking" (Franklin Associates, Ltd., 1992).

Table 6-1 provides an example of energy consumption data for two different LCA production processes. Energy usage is broken down by the different components of a product, the packaging processes, the distribution of the product to the retail sector, and the final disposition of the product. Based on a "least emissions" criterion, the two processes are ranked by total energy usage. System 1 uses approximately 16.8 million Btu, and System 2 uses approximately 13 million Btu. Thus, System 2 is ranked higher (in terms of energy consumption) than System 1. The sensitivity is expressed as the ratio of the difference in total energy consumption (16.783 - 13.186 = 3.597 million Btu) over the amount of energy consumed by each process component.

For example, for the "Distribution to Retail" component of System 1, the percent error is 3.597/1.030 = 3.492 or approximately 350 percent. This indicates that energy consumption in the retail component of System 1 would have to change, or be in error, by approximately 350 percent to reverse the rankings of the two systems. Given that the data are unlikely to be in error to this order of magnitude, the "Distribution to Retail" component of system 1 would not be considered important (or sensitive) to the overall results. If, however, the error was 5 percent rather than 350 percent, this would mean that a 5 percent error in the data could reverse the rankings of the two systems. Because it is conceivable that any given LCA data source could be in error by 5 percent, small percent error calculations would indicate where data quality resources should be focused.

Although straightforward, this approach has some limitations. First, it is applicable only to comparative LCAs. If a single product or process were under evaluation, there would be no second system to use for comparison. Second, the percent error calculations are based on the data obtained for the LCA. If different data were collected, the percent error calculation would be different. It is fair to state, however, that analysts try to obtain "the best data available" when conducting an LCA. Thus, some degree of confidence could be placed in these calculations. If LCA data are collected and assessed pursuant to the data quality framework outlined in Chapter 5, the percent error calculations would carry a fairly high degree of confidence. Third, the percent error calculation evaluates process components separately when, in actuality, each component is part of a complex industrial system. Therefore, calculating a simple ratio, or percent error, may fail to show the interrelationships between the many components of an industrial process.

Table 6-1. Energy Sensitivity Analysis on Two Production Systems

System Components	Energy Consumption (million Btu)		Percent Error Needed to Reverse Total Ranking
System #1			
Component 1	4.200		86
Component 2	6.300		57
Component 3	0.555		649
Component 4	0.921		391
Component 5	1.300		277
Subtotal:		13.276	
Primary Packaging		1.200	300
Secondary Packaging			
Corrugated	0.200		1,800
Stretch Wrap	0.050		7,200
Subtotal:		0.250	
Filling and Packaging		0.985	365
Distribution to Retail		1.030	350
Disposition		0.042	8,571
Total		16.783	21
System #2			
Component 1	3.600		100
Component 2	3.200		113
Component 3	0.640		563
Component 4	1.350		267
Subtotal:		8.790	
Primary Packaging		2.300	156
Secondary Packaging			
Corrugated	0.260		1,385
Stretch Wrap	0.032		11,250
Subtotal:		0.292	
Filling and Packaging		0.752	479
Distribution to Retail		0.996	361
Disposition		0.056	6,429
Total		13.186	27

Source: Franklin Associates, 1992.

6.2 UNCERTAINTY ANALYSIS

Uncertainty analysis is used to determine how various sources of uncertainty in parameter inputs, such as incomplete information, variability in a factor, or the structure and simplifying assumptions used in the creation of a model, influence model outputs. Analysts use uncertainty analysis to provide an understanding of the importance of a data source or model to a composite analysis, or as a decision tool for determining whether to acquire additional information (Morgan and Henrion, 1990). Both applications of uncertainty analysis may be applicable to LCA data. Uncertainty analysis techniques could be used to further indicate where data quality resources should be focused, and to determine the total uncertainty (or error) in the final LCA results.

The general principle of uncertainty analysis is to assign probabilities to uncertain parameters and then use various statistical or mathematical techniques to determine the uncertainty in model outputs. In general, probabilities are assigned based on past empirical data, or expert or subjective judgment (Keeney and Raiffa, 1976). Sections 6.2.1 and 6.2.2 discuss various sources of uncertainty and methods used to propagate and analyze uncertainty.

6.2.1 Sources of Uncertainty

The process of determining sources of uncertainty involves asking a properly worded question for which the answer is uncertain and itemizing all the sources of uncertainty that contribute to overall ambiguity (Finkel, 1990). Sources of uncertainty potentially applicable to LCA data include (1) random error and statistical variation, (2) systematic error, (3) variability, and (4) approximation.

Random Error and Statistical Variation

The most commonly studied and best understood cause of uncertainty results from random error in direct measurements of a quantity. Random error results from imperfections in the measuring instrument and observational technique (Morgan and Henrion, 1990). Taking repeated measurements can help reduce the effects of uncertainty associated with random error.

In the LCA context, an analyst can detect random error if primary, statistically sampled data are used, or if a statistically sampled secondary source contains a complete description of the methods used to collect the data and the data are nonaggregated. In these situations, the process of describing uncertainties is rather simple because it involves calculating statistical measures such as a standard deviation and/or confidence intervals.

Systematic Error

Unlike random error and statistical variation, systematic error results from some inherent flaw in the data collection process (Finkel, 1990). For example, systematic error may be caused by improper calibration of measurement instruments, or the continuous misreading of a measurement instrument, due to such factors as poor training or the angle at which the gauge is read. If a survey is involved, however, questions can be phrased such that an unintended answer is consistently obtained.

Systematic error can be reduced by carefully designing an experiment. In this context, an experiment does not imply that laboratory work be conducted. Instead, an experiment can be the procedure of gathering data. However, some degree of systematic error will still exist, no matter how well the experiment is designed. The statistical methods available for assessing the uncertainty due to random error do not apply to assessing any systematic error that could not be eliminated by properly designing the experiment. Rather, subjective probability distributions must be assigned to the various possible effects of the systematic error.

In assigning a subjective probability distribution to a series of possible effects, an analyst may use the Bayesian view of probability. From this stand point, a probability of an event is the person's degree of belief that it will occur given all of the relevant information currently know to that person (Morgan and Henrion, 1990). In an LCA context, expert opinion is the likely method for developing these subjective probability distributions. Once the distribution has been developed, methods for propagating and analyzing the effects of uncertainty can be employed.

Variability

Variability refers to the natural fluctuation in the measurement of variables over time or space. Examples include the salinity of sea water, phosphate concentrations in waste water, and the heights of 20-year-old Americans. Assessing the uncertainty caused by the variability of a quantity can be simple provided that enough data are available on the quantity to form a frequency distribution. A frequency distribution expresses the number of times a variable takes on a specific value, thus it shows which values have occurred more often. Associated with a frequency distribution is a relative frequency distribution, which expresses the percentage of time a variable has taken a specific valued.

If LCA data are aggregated, it may be impossible to construct a frequency distribution. However, if a frequency distribution is available and is considered to be appropriate for assessing uncertainty, the uncertainty about a quantity can be represented by a probability distribution with the same parameters as the frequency distribution. Analysts may also assign ranges with defined boundaries to each uncertain variable. Methods such as Gaussian approximation and Monte Carlo analysis can then be used to analyze the effects of parameter uncertainty.

Approximation

Uncertainty due to approximation occurs when models are used or created. Designing a model that completely represents that process or system of concern is virtually impossible. Therefore, certain approximations and assumptions must be made in order to present a viable option to other methods of data collection.

Specific sources of uncertainty in a model are (1) model structure, (2) abnormal conditions, (3) excluded variables, and (4) surrogate variables (Finkel, 1990). Inappropriate model structure can lead to results that are not representative of the process being modeled. Abnormal conditions may prevent the generalization of a model to the system of interest. Model verification and validation can help to find areas in which uncertainties may be reduced by denoting why the model structure is inappropriate or describing any abnormal conditions that may exist.

Excluding variables can increase the uncertainty associated with a model because one or more variables that have a strong influence on the outcome may be dropped out for computational efficiency. For an LCA, sensitivity analysis or expert opinion could be used to determine which variable(s) might be considered for exclusion from the model.

Surrogate variables also have uncertainty associated with them because they do not measure the exact quantity of interest. However, a surrogate variable can actually decrease the overall level of uncertainty if measurements of the quantity of interest are difficult to obtain. The level of uncertainty associated with the use of surrogate variables can possibly be decreased by increasing the mathematical complexity of the parts of the model containing the surrogate variable, but one needs to determine if the additional complexity adds other forms of uncertainty to the model (Finkel, 1990).

With respect to LCAs, uncertainty due to approximation may be assessed in the industrial process model used to generate LCA results, or in a primary or secondary modeled data source used as an input to the LCA.

6.2.2 Methods of Determining Uncertainty Propagation and Analyzing Uncertainty

Following the assignment of probability distributions or ranges to a series of uncertain events, either by use of frequency distributions, Bayesian methods, or subjective or expert judgment, uncertainty propagation and analysis takes place. Uncertainty propagation involves determining how the uncertainties involved with inputs affect the uncertainty of an output. There are a variety of methods for the propagation and analysis of uncertainty. Two commonly used methods are (1) first-order Taylor series (Gaussian) approximation methods and (2) Monte Carlo simulation. A variant on the Monte Carlo simulation, known as "Latin Hypercube Sampling," is also discussed in addition to the traditional method of random sampling used in Monte Carlo simulation.

The First-Order Taylor Series (Gaussian) Method

The simplest uncertainty analysis technique is the Gaussian, or First-Order Taylor series, method which considers both sensitivity and uncertainty. Like sensitivity analysis, low and high values, representing plausible ranges or probability distributions, are selected, while holding all other variables constant, to determine the relative uncertainty associated with each variable and thus with total outputs. As indicated by Morgan and Henrion (1990), this uncertainty propagation method combines the sensitivity of the model outputs with the uncertainties associated with each input to determine the uncertainty in model outputs.

Once the probability function has been developed, partial derivatives of the dependent variable with respect to each explanatory variable are calculated. These partial derivatives are the rates of change of the dependent variable with respect to the unit change in an explanatory variable, provided all other explanatory variables are held constant. These partial derivatives are then evaluated for a nominal, or base-case scenario, which are initial "best guess" values for the explanatory variables.

Following the evaluation of the partial derivatives, each value is squared and multiplied by the variance of the explanatory variable involved in the evaluation of the partial derivative. If the explanatory variables are independent of each other, the quantities calculated above are summed to produce an estimate of the variance of the dependent variable. If not, the calculation can be used to produce the covariance of each pair of explanatory variables. The formulas for these calculations are presented in Morgan and Henrion (1990).

Monte Carlo Simulation

Monte Carlo simulation involves simulating a system by randomly selecting values for each explanatory variable in a function as described in the Gaussian approximation section, then plugging the values into a functional equation and producing a simulated output value. Through the use of computers, the process is repeated hundreds or thousands of times to generate a simulated distribution for the output variable (Morgan and Henrion, 1990).

The fact that values are selected at random for each of the explanatory variables implies that distributions for each of these variables must have been developed. Once again, these may have been developed by the use of frequency distributions, Bayesian methods, or expert or subjective judgment. The simulated values are assumed to be independent of each other, which allows for easier statistical analysis.

A recent application of the traditional stratified random sampling method used in Monte Carlo simulation is know as Latin Hypercube Sampling (LHS). In LHS, the distribution of an explanatory variable is divided up into a number of equiprobable intervals equal to the number of samples taken. Then, a point is selected at random from each of the intervals. This produces simulated examples that are more uniformly spread out over the distributions of the explanatory variables (Morgan and Henrion, 1990; Iman and Heltan, 1988; Iman, 1987; DOC, 1985). The increased use of LHS has resulted because the simulation can more accurately represent the parameters of the distribution than simple random sampling.

6.2.3 Applicability of Uncertainty Analysis to LCA Data Quality

Like deterministic sensitivity analysis, the simplest uncertainty analysis technique, the Gaussian Method, may be most applicable to an evaluation of LCA data quality. The computational requirements and information obtained from the more complicated uncertainty techniques may go beyond what could reasonably be expected for an LCA data quality evaluation. The Gaussian method, however, allows for the assignment of ranges or probability distributions for uncertain model inputs to assess the composite uncertainty in model outputs. This simple uncertainty analysis technique could reveal which sensitive variables also are-or are not-uncertain. If parameters identified as most important (or sensitive) to LCA results also are highly uncertain, LCA practitioners may want to focus data quality resources on these parameters. As indicated by Morgan and Henrion (1990),

> when a decision must be made about whether to expend resources to acquire additional information, in general, the greater the uncertainty, the greater the expected value of additional information.

As stated above, error propagation techniques, such as monte carlo analysis, also could be used to determine the total uncertainty in final LCA results.

CHAPTER 7
METHODS TO COMPENSATE FOR MISSING DATA AND DATA DEFICIENCIES

In the process of generating or gathering data—primary or secondary—various problems can arise in the data set. This chapter discusses missing data (actual missing values) and data deficiencies (weaknesses in measurement techniques, sampling methods, etc.). Mathematical techniques (such as imputation and weighting) used to compensate for missing data and data deficiencies are discussed below. The final section discusses a meta-research technique for combining data from disparate sources.

The methods discussed in this chapter are suitable for addressing problems with LCA data. The methods do vary in complexity, however. Some methods require the use of expert opinion or deductive logic while others require the use of advanced statistical techniques. When applying these techniques to LCA data, it is advisable to consult with experts in the applicable methodological field.

7.1 MISSING DATA AND DATA DEFICIENCIES

One problem that occurs in conducting an LCA are different levels of missing data. First, no data may be available for a given industry, facility, product, or process. Also, data may be available for a product but not for all the components of the process. Lastly, a data set that was derived from a survey may have missing data due to nonresponse by facilities receiving the survey (unit nonresponse) or missing data for specific items on a questionnaire (item nonresponse) (Lepkowski et al., 1987).

Missing data can occur for other reasons. For example, a data set with values on air emissions may have a previously determined threshold level below which values are marked with a code instead of the actual value. Other values may be missing on the basis of a second variable, that is, if information for a variable is not available, values for other variables that are dependent on the initial variable may also be indeterminable (Azen et al., 1989). In some cases, transcription errors may cause values to be skipped inadvertently. In short, missing data are data that someone attempted to collect; however, for some reason, the data values are missing.

Unlike missing data, data deficiencies are associated with the methods involved in collecting, synthesizing, analyzing, and describing data. Some areas that cause data deficiencies include sampling design, data collection methods, aggregation techniques, description of variables in data sets , and measurement methods (Plewa et al., 1988) . For example, if data were collected on electricity usage for all firms within an industry, but the reported data were rounded up to the nearest 100 kWh before any analysis, measures such as the sum, sample mean, and sample standard deviation would be biased.

7.2 METHODS TO ADJUST FOR MISSING DATA AND DATA DEFICIENCIES

Various methods have been introduced to adjust and analyze data sets that are beset by missing values or deficiencies. Despite all of the techniques, the most effective method may be to collect more data. The time and money needed to design or continue data collection efforts for an LCA may be too restrictive. Therefore, this section evaluates other methods that may be used to fix the problems associated with missing data or data deficiencies.

This section examines a series of methods to handle missing data. One method, known as imputation, is composed of a broad spectrum of techniques involving proxies, logical deductions, and statistically based procedures, or a combination of the methods. The imputation techniques examined are (a) proxies, (b) deductive imputation, (c) mean imputation overall, (d) random imputation overall, (e) mean imputation within classes, (f) random imputation within classes, (g) cold-deck imputation, (h) hot-deck imputation, (i) predicted regression imputation, and (j) random regression imputation. The second method involves weighting the answers for survey respondents in order to compensate for nonrespondents.

Each of the methods can be applied to LCA data. The methods have different strengths and weaknesses in terms of ease of use, cost, the need for a statistician, and potential effects. Sensitivity analysis, which is discussed in the previous chapter, can be used to determine which variables are more important to the analysis. If variables determined to be less important contain missing data or data deficiencies, these mathematical techniques could be useful for handling the problem. As indicated previously, the best fix for an LCA data problem is to collect actual facility-specific information, if possible.

7.2.1 Imputation

Imputation is a general method used to adjust for item nonresponse, which occurs when a survey respondent fails to respond to all of the questions, as well as for many other varieties of missing data. Simply stated, imputation is the procedure of replacing a missing value with a value that is considered to be a reasonable proxy or substitute (Lepkowski et al., 1987). A range of proxies exist, from an ad hoc value developed from prior experience or logical deduction, to a predicted value from an empirically derived model.

Logical Proxies

One method of replacing missing data is to find a "reasonable" substitute for the missing information. Logically developed proxies are one viable substitute for missing data, especially when there are no data on a given component of the process or product of interest. For example, if no data exist on water releases for a specific facility within an industry, certain facilities in the industry for which the data do exist could be evaluated for use as a proxy for the facility of concern. Similarly, if data were missing for an entire industry, an analyst could use data for the industry determined to be most similar to the industry being examined. Developing proxies requires expert opinion to determine the validity of the proxy.

Deductive Imputation

Deductive imputation, which involves examining patterns in the data to draw conclusions about missing data values, has potential for determining missing LCA data values. Suppose an analyst is examining one of the raw materials that goes into making a specific product. In making the product, a co-product and waste releases are created. Portions of the raw material are transformed into the product, the co-product, and the waste releases. Now suppose that the analyst has a data set for an industry that used 500,000 kg of the raw materials, of which 400,000 kg became part of the product and 37,000 kg went into solid waste. Using deductive imputation—taking the total amount of inputs and subtracting all the known amounts of outputs—the analyst could deduce that 63,000 kg of the material went into the co-product.

In the above example the analyst would need to consider whether a mass-balance equation would suitably represent the process. The important criterion required to use this method is that there be some distinguishable pattern in the data or the process such that there is a high likelihood that the calculated value is either the correct value or very close to the correct value (Kalton and Kasprzyk, 1982).

Mean Imputation Overall

The mean imputation overall method involves taking the mean of the known data values and substituting this mean for each of the missing data values (Kalton and Kasprzyk, 1982). For example, if a data set contained 500 reported values and 100 missing values for the amount of a chemical released into a waste stream, an analyst could calculate the average of the 500 known values and substitute this value for the 100 missing values. Analyses can then be performed using all 600 data points.

This method should be used with caution given that the variability in the unknown missing values is not taken into account (Rubin, 1987). Because the sample mean is used for the missing data points, the sample variance and standard deviation will, most likely, be significantly understated. The results also may be biased to the extent that missing values differ consistently from those present.

Random Imputation Overall

In contrast to the mean imputation overall method, the random imputation method accounts for some of the variability in the unknown data values (Rubin, 1987). Each missing value is replaced with a data value selected at random with replacement from the respondent data. Using the chemical release example mentioned in the previous section, each of the 500 known values could be assigned a probability of 1/500 (using a random number generator, random digit table, balls in a hat, etc.). One value is then chosen as the 501st data value. The value should not be removed from possible further selection as this complicates the analysis. The procedure is continued until all 100 missing values have been imputed.

Mean Imputation Within Classes

The division of a sample into imputation classes benefits from similarity of the items within a class. These classes can be determined by evaluating the subjects and by expert opinion, or they could be determined by similarities in other variables (Cox, 1981; Kalton et al., 1982). For each imputation class, the mean of the respondents' values is calculated. Each calculated mean is used to replace the missing data in its own class. As in the mean imputation overall method, using the sample mean as a replacement may result in biased statistics in the analysis.

Referring back to the chemical example, an analyst may determine from an examination of the data or expert opinion that the amount of the chemical released varies significantly from one industry to another. Suppose that four industry classifications within the data set affect the amount of the chemical released. These classifications would be the foundation for the imputation classes. The mean imputation procedure would then be used within each class and the four classes analyzed separately.

Random Imputation Within Classes

Random imputation within classes combines the random imputation overall methodology with the formation of imputation classes. After forming imputation classes, the analyst replaces missing values with values selected at random from the respondents' values within the class currently being imputed (Kalton et al., 1982). As in the case of comparing the random and mean imputation overall methodologies, random imputation within classes accounts for some of the increase in variability that is not accounted for by the mean methodology.

Cold-Deck and Hot-Deck Imputation

Cold-deck imputation uses values from a prior distribution as replacements for missing values in the data set of concern. This method requires that at least one data set exist that is similar to what is being measured in the data set with missing values. The imputed values can be selected by using randomization or systematic methods. In addition, the data are often divided into imputation classes (Chapman, 1976). As of 1981, cold-deck procedures have rarely been used because of the criticism that current data were not being used for imputation procedures (Chapman, 1976; Cox, 1981). We suggest that these procedures not be used for LCAs.

Unlike cold-deck methods, hot-deck imputation uses only the data set for which the missing values are being imputed. As in the cold-deck procedure, imputation classes need to be formed. An initial value (or cold-deck) based on previous or current data or expert opinion is derived for the variable of concern. The records are then analyzed sequentially. If the first data value is present, it replaces the cold-deck value, thus becoming the hot-deck. If not, the cold-deck is used as the imputed value for the missing value. This procedure is continued, with a reported value replacing the current hot-deck, until all of the missing data values have been filled in.

Hot-deck procedures could possibly be used in conjunction with published data that have missing values. For example, if an analyst was using a database to determine energy usage associated with transportation in a given industry, and the values for the 6th, 27th, and 65th companies in a specific imputation class were missing, they would be replaced by the 5th, 26th, and 64th values in that class, respectively. However, the use of expert opinion and logical proxies may produce more accurate values for the missing data.

Predicted Regression Imputation

This method is somewhat similar to the deductive method, in which some function of the auxiliary (independent) variables is used to predict a missing value. In this method, a regression model is developed in which changes in the variable with missing values are described by changes in other (independent) variables that have an effect on the variable of interest, using only subjects or units for which all of these values have been reported. Then, the values of the independent variables for cases missing the dependent variable are substituted into the regression, thus creating a predicted value for the missing value (Kalton and Kasprzyk, 1982).

This method can be useful if the relationship between the variables is not easily determined by inspection or expert opinion. For instance, suppose changes in the amounts of any of ten inputs change the amount of a certain release. One must not only determine how a change in one of the inputs affects the release amount, but also how all possible simultaneous changes of two or more inputs affect the release amount. A statistician would be required to develop an appropriate regression model.

Random Regression Imputation

The final imputation method is an extension of the predicted regression imputation in that the entire predicted method is used; however, each imputed value has a residual (random) term added to it.

A residual is the difference between the observed and predicted value of the dependent variable for specific values of the independent variables. Residuals provide some notion of the predictive error of the model. Because a regression model is used to predict values for missing data, a residual cannot be calculated. Rather, a residual can be chosen to assist in assessing predictive error. There are both statistical and deductive methods for choosing residuals. For instance, if a case with no missing values and a case missing a value have similarly valued auxiliary variables, the residual value for the case with no missing values can be used as a proxy for the residual of the imputed value.

The statistical methods of imputing a residual are complex. The following examples are provided without an explanation of the underlying statistical theory. The interested reader is directed to Kalton and Kasprzyk (1982). One method involves choosing a residual at random from a distribution assumed to represent the residuals. If the residuals are assumed to be of equal variance (homoskedastic) and normally distributed, they can be chosen at random from a normal distribution with mean zero and variance equal to the residual variance from the regression. In a more general example, if the residuals are assumed to come from the same, but unknown, distribution they can be chosen at random from the respondents' residuals (Kalton and Kasprzyk, 1982).

The imputation methods discussed above may be applicable to LCA data. However, denoting any imputed data and the uncertainty involved with the use of these methods is very important. These methods may best be applied to LCA parameters deemed less important to the analysis. While they "fix" or "compensate" for data problems, they do not enhance data quality or replace missing data with more applicable (or detailed) facility data.

7.2.2 Weighting Methods

One method commonly used to compensate for unit nonresponse in surveys, which occurs when a person asked to respond to a survey fails to do so, is to develop weights to inflate the responses of units that do respond. The various weighting methods correspond to the statistical sampling methods used in choosing the survey participants.

An example of a weighting method could involve surveying 500 companies on energy usage. If only 450 companies respond, the analyst examines other information about the companies to see which responding companies are most similar to each nonresponding company. If one responding company is most similar to 5 nonresponding companies while another is most similar to 7 nonrespondents, these responding companies would be assigned weights of 6 and 8, respectively. The weights are calculated by summing 1 (for the responding company) and the number of nonresponding companies deemed to be most similar to the responding company. Each of the responding companies that were not considered to be the most similar to one or more nonresponding companies would each receive a weight of one. The sum of the responding companies' weights should then equal 500 (Rubin, 1987). Because of the complex statistical methods involved, the estimation procedures associated with this or any other weighting method are beyond the scope of this paper. The interested reader is directed to Little and Rubin (1987).

The use of weighting methods by an LCA analyst would likely be rare, as very little of the primary data are gathered using surveys of companies or facilities. However, if a secondary data source, such as an EPA database, used sampling methods to gather data determining the validity of any weighting methods used in assembling the database may be important. This would require consulting a statistician and obtaining a description of both the sampling and weighting methods.

7.3 META-RESEARCH

Meta-research combines information or conclusions from disparate studies to compare study results, or to develop general conclusions based on the information in each of the studies. There are two different classifications of meta-research. The first, which is known as meta-analysis, uses statistical techniques for the review and combination of data from a number of original studies. The second method, referred to as a "propositional inventory," involves collecting verbal conclusions from studies in which the original data are not available. The qualitative conclusions are then analyzed to determine if a general conclusion can be made about the subject of interest.

It is unlikely that either meta-research method is applicable to LCA data. First, the goal of meta-research is to make conclusions about relationships between different variables by using previously performed research. The relationship could be of a cause-and-effect nature, or where two or more variables are associated with another variable. In an LCA, the goal is to delineate the inputs and the outputs associated with a product or process of interest. If any conclusions are made within the framework of an LCA, such as one process produces less solid waste than another, the conclusion is made based on the data values within the LCA. Second, meta-analysis is possible if the original empirical data are available to the meta-researchers. Because much of the data used in an LCA are aggregated, and primary data are typically not available, meta-analysis would be very difficult to perform.

Meta-research may, however, be useful to synthesize results from various life cycle impact assessments to develop general conclusions about a process or product.

Suppose that several companies or organizations performed separate LCAs on the same product. Each study assumes the use of coal as the energy source in the production of the product. In each LCA, the impact analysis determined that the coal used to generate energy has the most severe environmental impact. Combining the studies using meta-research procedures could reveal the most likely impacts. The application of meta-research to an evaluation of IA results is an issue requiring further research and discussion.

CHAPTER 8
GOOD DATA QUALITY PRACTICES FOR LIFE CYCLE ASSESSMENT DATA

This chapter summarizes the information provided in this document into a set of good data quality practices (GDQPs) for LCAs. GDQPs incorporate an eight-part process for determining LCA data quality. These steps are highlighted in Figure 8-1.

DQGs can be used as LCA data quality performance criteria. As discussed previously, DQGs are specifications for the adequacy of data and should be in the form of a qualitative statement of the type of data needed for a particular category of LCA data. With respect to LCA data, DQGs can be developed for each parameter used in the inventory, the most important parameters only, or the LCA overall. Regardless of the approach, DQGs can serve as performance criteria, or relative rankings, to provide an analyst guidance on the level of data quality needed for an LCA. DQGs, if documented in an LCA, also can indicate to users of the LCA which parameters are considered more important from a data quality perspective. DQIs then can be selected and used to determine whether the DQGs have been met.

DQIs are benchmarks for evaluating data quality. LCA data quality is influenced by the quality of the data source, and any assumptions and calculations used to generate LCA data. Data quality can be determined qualitatively by evaluating LCA data sources against various DQIs. This document, however, recommends a more systematic approach to assessing LCA data quality.

Chapters 4 and 5 outline a framework for a structured evaluation of LCA data quality. The framework indicates which DQIs are applicable to different categories and forms of LCA data, and includes a mechanism for calculating data quality scores for each LCA parameter. By documenting the results and scores in an LCA, the analysis provides users of the material a basis to make judgments about LCA data quality.

Where appropriate, sensitivity analysis should be used to assess the importance of different LCA inputs on model outputs. As indicated in Chapter 6, determining which LCA variables are most important to the analysis would provide an indication of where data quality resources should be focused.

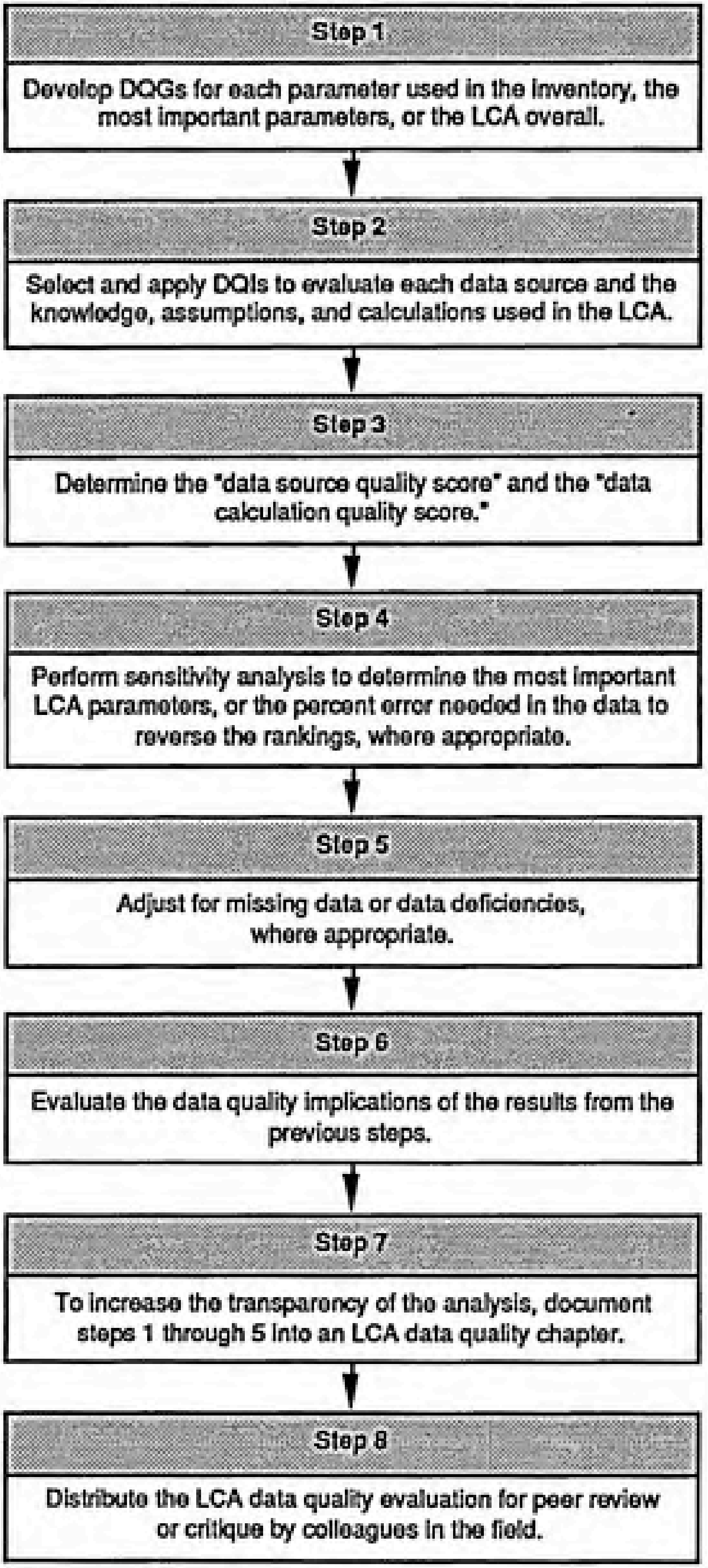


Figure 8-1. Good Data Quality Practices (GDQPs)

Sensitivity analysis also can be applied to comparative LCAs where the basis for the analysis is the least emissions approach. This approach first ranks the two systems and then determines the percent error needed in the data to reverse the rankings. There are limitations with this approach. It is applicable to comparative LCAs only, and the percent error calculations may be questioned based on the data used in the study. Regarding the latter, if different data were used, the percent error calculations also would be different. A good practice would be to evaluate comparative LCA data against the data quality criteria provided in Chapter 4 and then determine the percent error in the data necessary to reverse the rankings. If LCA data quality is better understood, the information provided from the percent error calculations could be regarded with greater confidence.

Although more difficult mathematically, uncertainty analysis also may be used to help focus data quality resources, and/or to identify the total uncertainty in final LCA results. Unlike sensitivity analysis, uncertainty analysis allows an analyst to evaluate the uncertainty in and between input variables and to assess the effect on the overall uncertainty on model results. If highly sensitive variables are also very uncertain, it would be appropriate to focus data quality resources to improve the information for these parameters. Furthermore, given the diverse data types and sources used in LCAs, it is appropriate to provide users of LCAs with an indication of the overall uncertainty in the final data values.

LCA data sources may contain missing data or data deficiencies. The best way to fix missing data and data deficiencies is to collect new data. However, a variety of mathematical techniques (e.g., imputation and weighting) are available to address these problems. The results of sensitivity analysis can be used to determine whether new data should be collected or if one or both of the mathematical techniques discussed in Chapter 6 should be applied. A sensitivity analysis can indicate which variables are more important to the analysis. If the most important variables contain data deficiencies, the analyst should consider collecting additional data. However, imputation or weighting-type methods may be applicable to adjusting those variables determined through sensitivity analysis to be less important. If LCA data have been adjusted, the analyst may want to consider assessing the impact of the modification, e.g., whether the variability in the data increased, decreased, or stayed the same.

Documenting data quality determinations in LCAs is extremely important. Previously published LCAs have provided minimal discussion about data quality.

Without documenting the data sources used in an LCA, and the criteria against which each source was assessed, the credibility of the numbers may be questioned. Detailing all data sources, assumptions, and calculations employed in the LCA will increase the transparency of the analysis to reviewers and users and thus enhance its overall credibility. Additionally, the results of a DQI analysis and the scoring system should be fully documented to indicate the level of data quality associated with each LCA parameter or, at a minimum, the most important LCA variables.

Final LCAs should indicate whether the material was peer reviewed or distributed for review by colleagues in the field. The report also should detail the results of such an effort. Obtaining general agreement from peer reviewers or colleagues about the quality of the LCA data, and the assumptions and calculations used throughout, will lend significant credibility to the analysis. The importance of receiving outside acceptance of LCA results should not be underestimated.

APPENDIX A
QUALITY ASSURANCE/QUALITY CONTROL METHOD

QUALITY ASSURANCE/QUALITY CONTROL METHOD

EPA's quality assurance program requires that all data collected for or by the Agency be "scientifically valid, defensible, and of known precision and accuracy" (EPA, 1989). The system under which the quality of environmental data are reviewed is referred to as Quality Assurance and Quality Control, or QA/QC. The QA/QC scheme typically is applied to data collected in a statistical manner, such as environmental sample collection (e.g., soil, water, or air samples) or laboratory analyses. The QA/QC methodology is employed across all EPA programs when sampling and analysis of environmental data are undertaken (Barth et al., 1989; NRC, 1988; EPA, 1989; Mickler & Medlarz, 1987; and Neptune et al., 1990).

> Quality assurance is the system of activities required to provide a quality product.

> Quality control is the system of activities required to provide information as to whether the quality assurance system is performing adequately.

Quality assurance is defined as "the system of activities required to provide a quality product" whereas quality control is defined as "the system of activities required to provide information as to whether the quality assurance system is performing adequately" (Barth et al., 1989; and NRC, 1989). There are two primary aspects to the QA/QC process: developing Data Quality Objectives (DQOs) and preparing a Quality Assurance Project Plan (QAPJP). Barth et al. (1989) describes DQOs as "qualitative and quantitative statements developed by data users to specify the quality of data needed from a particular data activity." DQOs, which place limits on the level of acceptable uncertainty in a data set, are used as performance criteria for assessing overall data quality (EPA, 1986a). The QAPJP outlines the necessary procedures "to assure that the needs expressed by the DQOs are met" (Barth et al., 1989). The most significant of these two parts of the QA/QC process is the development and implementation of DQOs. Consequently, most of this section is devoted to a discussion of DQOs.

A.1 DATA QUALITY OBJECTIVES

> Data Quality Objectives are statements of the probability of making an incorrect decision, based on the data collected.

DQOs are statements of the probability of making an incorrect decision based on the data collected. DQOs are also referred to as the level of uncertainty an analyst is willing to accept in the data. Data quality indicators (DQIs), such as precision, bias, and representativeness, are used within the DQO process to assess the quality of environmental data. As defined by EPA, there are three stages in the process of developing DQOs: (1) identifying or defining decision types; (2) identifying data uses and needs; and (3) designing the data collection program. Each stage of the DQO process

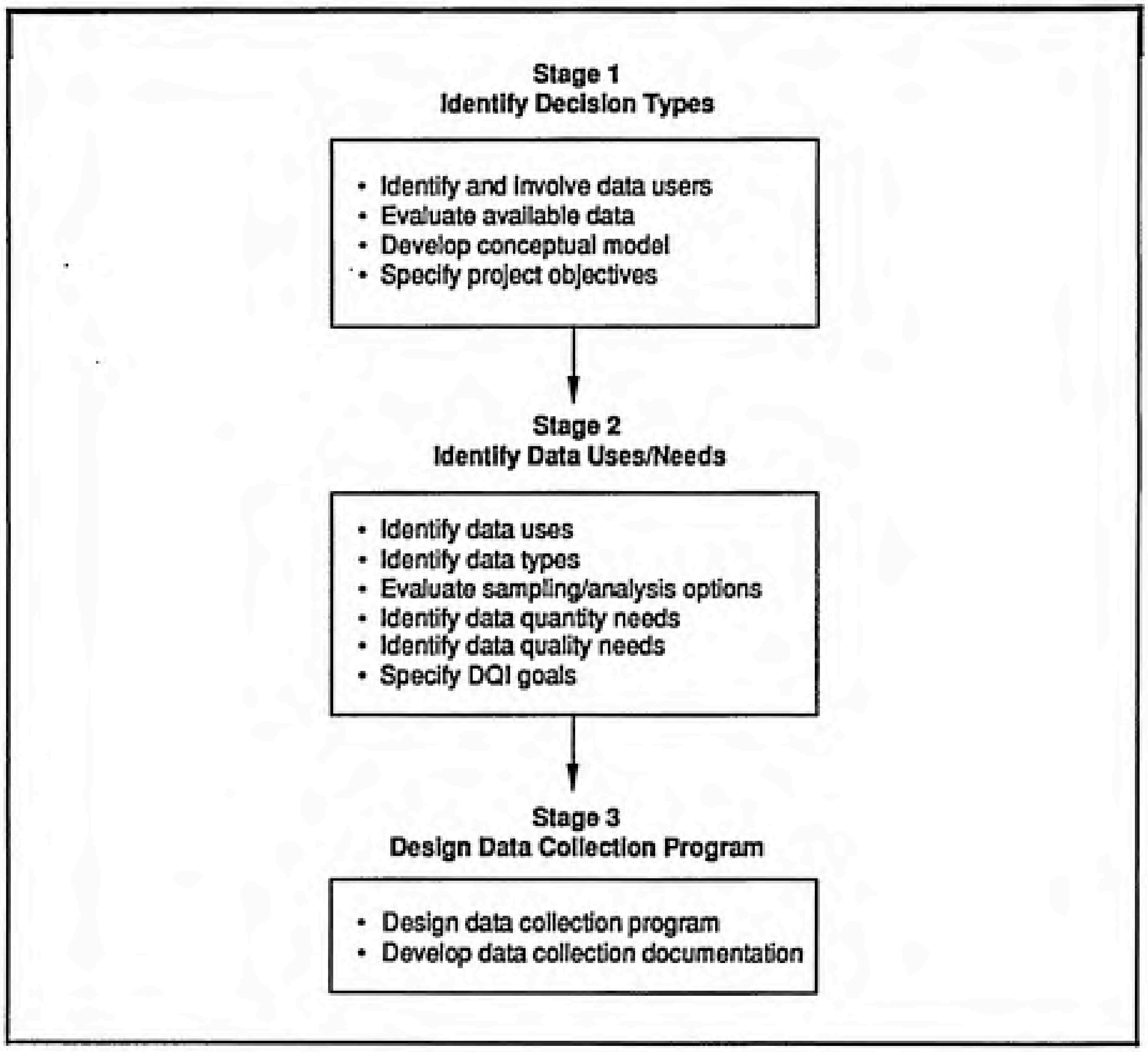


Figure A-1. The Stages of the DQO Process
Source: Barth et al., 1989

includes multiple tasks (see Figure A-1). Rather than reviewing each task, the information provided below discusses those aspects of the DQO process that could be applied to an assessment of LCA data quality.

Stage I: Identifying Decision Types

Stage I involves identifying and involving data users, reviewing available data, developing a conceptual model of what is being measured, and defining the consequence(s) of an incorrect decision. QA/QC procedures typically are applied to environmental sampling, such as the collection and analysis of soil samples from hazardous waste sites, and the analysis of air samples from pollution control equipment. The main objectives at this stage are to

- review all existing site data,
- define the decisions that will be made with the data, and
- specify who will use the information.

Two Stage I tasks can be applied to LCA data: reviewing available background information and defining the consequence of an incorrect decision.

The first part of Stage I requires evaluating all available background and existing data. From a QA/QC perspective this means, prior to initiating a sampling effort, evaluating all available information to determine the degree to which sampling is needed. EPA's QA/QC policy recommends assessing the quality of these data sources against

- the age of the data sets and their comparability,
- the precision and accuracy of the data,
- the sampling design and accuracy of the data,
- the methods used to collect, preserve, handle, and transport the samples,
- the analytical methods used to measure the pollutant,
- the detection limits for the methods, and
- the QC measures used by the laboratory and field team (Barth et al., 1989).

This task is relevant to LCA data in that it identifies indicators against which data quality can be assessed. Each DQI listed above is applicable to primary data, that is, data collected through sampling and measurement methods. For secondary data, however, additional DQIs are needed (see Sections 4.3 and 4.4 for a detailed discussion of the DQIs that are applicable to secondary LCA data).

Defining the impact of an incorrect decision involves determining which error type would present a bigger problem. An error type is a statistical term that refers to the likelihood of an incorrect decision or, in this case, data resulting in a false positive (type I error) or a false negative (type II error). A type I error occurs when the analysis concludes that there is an effect when, in fact, the data were incorrect or misleading and the effect did not occur. A type II error is the reverse situation; it occurs when the analysis concludes that there is no effect when, in fact, the data were incorrect or misleading and the effect did occur. For example, decision-makers could be faced with evaluating whether an uncontrolled hazardous waste site should be remediated. A type I error would conclude that clean-up should occur when, in fact, the site did not need remedial action, whereas a type II error would conclude that clean-up should not occur when, in fact, the site posed enough of a risk to human health and the environment that it should have been cleaned up (Barth et al., 1987; Neptune et al., 1987).

Because QA/QC data are generated under a statistical protocol, it is appropriate to define DQOs in terms of type I and type II errors. Put more simply, this entails identifying which error type, a false positive or false negative, would present a bigger problem. In the hazardous waste example, a false positive could result in cleaning up a site when it should not have been cleaned up. The result would be an unnecessary expenditure of a significant amount of money. On the other hand, a false negative indicates that remediation is not necessary when, in fact, the site did need remediation. Based on the level of contamination, significant exposures could damage human health and/or the environment. In this example the false negative error would present a more serious problem.

Stage II: Identifying Data Uses and Needs

Stage II of the DQO process stipulates the criteria for determining the adequacy of collected samples. This involves

- specifying the level of certainty necessary to attain the objectives outlined in Stage I,
- determining data needs and types, including a consideration of time and resource constraints,
- evaluating and selecting appropriate sampling methods, and

- identifying DQIs for newly collected samples.

The second task (determining data needs and types) is applicable to LCA data. As indicated in the flow chart in Chapter 3, this step logically occurs after the completion of a comprehensive input/output chart. The third task (evaluating and selecting appropriate sampling methods) only applies to the collection of primary LCA data. The first and last tasks (specifying the level of certainty and identifying DQIs) are most pertinent to assessing LCA data quality. With respect to defining the level of acceptable uncertainty, Stage II requires assigning probabilities to the error types defined in Stage I. To assign probabilities, EPA (1991d) recommends

- determining the type I and type II errors for the total analysis and/or each individual parameter,
- ranking the error types in terms of their relative importance, and
- assigning acceptable probabilities of occurrence to each.

Probability assignments serve as yardsticks against which data quality can be measured. EPA recommends considering first situations that should never occur, such as not detecting a chemical that actually poses an environmental threat. These situations could be assigned a probability of 1×10^{-6} (i.e., there should be a one in a million chance that the data are misleading or incorrect). This indicates that the uncertainty associated with the data collected for that parameter should be kept to an absolute minimum.

Situations of relatively little concern, like a minor, infrequent, exceedence in a regulatory standard, should be considered next and assigned a probability such as 1×10^{-1} (one chance in 10). Once the extreme probabilities have been assigned, acceptable probabilities can be allocated to the other identified situations. EPA recommends documenting the results of this effort in a QA/QC plan either in text or in tabular form (EPA, 1986).

Stage II of the DQO process also requires identifying DQIs for the evaluation of newly collected samples. This is the cornerstone of the quality assurance program. The identification and analysis of DQIs helps determine an analyst's level of confidence in the data. In other words, DQIs serve as yardsticks, or measures of data quality.

The indicators typically used for QA/QC purposes are precision, accuracy, representativeness, completeness, and comparability. The DQIs are most applicable to primary data. A whole host of other DQIs are necessary for an evaluation of secondary data quality. Although the QA/QC DQIs can be used to assess secondary data, other indicators also need to be evaluated. These include consideration of whether the data source is thought to be acceptable by peers or colleagues in the field, whether the data collection methods are described or attainable, or whether the limitations associated with the data have been enumerated. In short, because secondary data typically are not generated under statistical procedures, other avenues need to be evaluated to understand how the data were collected, the purpose of the data, and the variability and limitations associated with the data.

Stage III: Designing the Data Collection Program

Stage III of the DQO process requires designing and implementing the data collection program. The outputs of this stage are documented plans for obtaining the data identified in the previous two stages (Barth et al., 1989). This stage of the DQO process is not completely relevant to inventory data. It refers to designing a sampling plan and detailing the plan in a document. Essentially, this would be applicable to the acquisition and analysis of primary LCI data. Clearly, this approach is not relevant to an assessment of LCA data quality if the information sources are secondary. However, as discussed in Chapter 8, the following aspects of this process are applicable to LCA data:

- identifying the level of data quality sought in the analysis (referred to as data quality objectives (DQOs),
- selecting and defining appropriate DQIs,
- evaluating LCI data against the DQIs to ensure that the DQOs have been met, and
- detailing the DQOs, DQIs, and the results of the analysis in a data quality section of an LCA.

A.2 QUALITY ASSURANCE PROJECT PLANS (QAPJPs)

EPA's quality assurance policy also requires that every QA/QC project be accompanied by a QAPJP. The plan contains the identified DQOs and a blueprint for conducting the quality assurance process. As indicated by EPA, the QAPJP is "the instrument for insuring that the DQOs are met" (Barth et al., 1989). As discussed above, incorporating a QAPJP-type requirement into an LCA is not recommended. What is recommended, however, is detailing this type of information in a separate data quality section in the LCA.

APPENDIX B
THE NUSAP METHOD

THE NUSAP METHOD

The Numerical, Unit, Spread (of value), Assessment (of value), Pedigree (NUSAP) method is used to assess the quality of a database by stating the spread of values associated with a certain entry and using a numerical code to describe various qualities related to the data and the data acquisition methods. In a database, each entry is typically listed without any notation denoting the variability or certainty of that value. As a result, many people assume that the data value is "exact." The NUSAP procedure for assessing uncertainty and quality of individual data in databases was developed to more accurately state the precision with which individual entries are known.

While the concepts used in the NUSAP framework are generally useful, the time required to complete the process could be excessive within the timeframe of an LCA. Because each data value or set would need to be evaluated under the NUSAP framework, a large database, such as EPA's Toxic Release Inventory (TRI), likely would require much more time and effort than is feasible within the time and resource constraints for most LCAs.

Various analyses have been performed using the NUSAP methodology. The following analysis, performed by Schaffhauser and Tonn at Oak Ridge National Laboratory (1991), assesses the uncertainty of data used in determining external costs from producing energy with various fuels. The example below includes Schaffhauser and Tonn's notation, which is slightly different than the NUSAP notation.

NUSAP Notation Adapted by Schaffhauser and Tonn		
(N, U_1, U_2): $(S_1, S_2[LB, UB], A[I_1, I_2, G, R])$: $(P[T, D, E, M])$.		
N	=	numeral (quantitative information)
U_1	=	unit(s) of measurement
U_2	=	statistic used for value, e.g., mean (ME), mode (MD), median (MN), lower bound (LB), upper bound (UB), expected value (EV), or no distribution (ND)
S_1	=	confidence level
S_2	=	S[LB, UB]
Assessment of value		
I_1	=	informative value based on spread
I_2	=	informative value based on application
G	=	generalizability to other applications
R	=	robustness of value over time
Pedigree		
T	=	theoretical basis (and application of theory)
D	=	data inputs
E	=	estimation methods
M	=	estimation metric

Despite the number of statistical terms in the NUSAP scheme, analysis of the data does not require the use of statistical methods. Generating a "NUSAP" spread is possible using expert opinion, or even educated guesses. The method used to generate the spread will be evaluated in the Assessment and Pedigree sections.

The Assessment and Pedigree components are both qualitative in nature. The Assessment section provides judgments about the data, rating their merit as pieces of information, while the Pedigree section assesses the quality of the data source. Assessment measures are all rated as low, medium, or high. This rating requires the subjective opinion of experts within the field. The first of the four Assessment measures is "Informative Value Based on Spread," which evaluates how much the uncertainty about a data value decreases before and after the study in which the data entry was conducted. "Informative Value Based on Application" considers how much the uncertainty about the entry affects an analytical result derived using the entry. In determining a rating for "Generalizability to Other Applications," an analyst must consider the worth of the entry in other applications. Lastly, "Robustness of Value Over Time" describes the expected validity of the data entry in the future.

The group of pedigree elements provided by Schaffhauser and Tonn is an example of many possible different groups of pedigree elements, depending on the specific information being analyzed. Values of 1 (worst) through 5 (best) are assigned to each pedigree element, although Funtowicz and Ravetz use a 0 through 4 scheme. The "Theoretical Basis" element assesses the strength of the theory and how well the theory is supported. The "Data Input" and "Estimation Methods" components measure the acceptability of the data and estimation methods used. The "Estimation Metric" component assesses the object measured in the production of the estimate. In other words, it can be employed to ask whether or not a proxy is used and, if so, how good the proxy is. Other elements that can be used in the pedigree component include "Theoretical Structures," "Level of Peer Acceptance," and "Colleague Consensus" (Funtowicz and Ravetz, 1990).

The NUSAP method has been applied in a variety of technical areas. An example provided by Funtowicz and Ravetz is the application of NUSAP to an analysis used to predict the competitive price of a barrel of oil. These results are translated below:

NUSAP Example: Predict Competitive Price of a Barrel of Oil	
Results: (6, 1983$/bl, mean) 90%, [3,11] [M, H, M, M] [1, 2, 3, 3]	
NUSAP Component	**Explanation**
(6, 1983$/bl, mean)	The mean predicted competitive price, stated in 1983 dollars, is $6/barrel.
90%, [3,11]	The 90% confidence interval is from $3 to $11. (This confidence interval was computed using statistical techniques. However, this fact was presented by the authors; it was not noted in the NUSAP scheme.)
[M, H, M, M]	
M	The level of uncertainty concerning the competitive price of oil was reduced a fair amount by the analysis.
H	The value of $6/barrel is highly informative for the application of determining whether or not the OPEC Cartel's price is competitive.
M	The estimate of $6/barrel is considered to be generalizable provided the current "relevant" conditions still exist.
M	The estimate of $6/barrel should be valid over a short length of time.
[1, 2, 3, 3]	
1	There is no real theoretical basis involved.
2	The data are considered to be poor.
3	The estimation methods are considered to be fair.
3	The proxy is considered to be fair.

APPENDIX C
DATA RELIABILITY INDICATOR

DATA RELIABILITY INDICATOR

The Data Reliability Indicator (DRI) is a system to evaluate the reliability of literature data on environmental process constants determined using experimental and analytical chemistry (Kollig, 1987). The method involves developing a series of questions, the answers to which provide information about four different components of the data collection process: analytical, experimental, statistical, and corroborative. Weighted scores are associated with affirmative answers to each question, then normalized scores are calculated for each of the four components. The four scores are then reported in the following fashion, (x, y, z, w). Summing the four normalized scores to produce an overall DRI value can present an additional measure of comparison; however, for reasons discussed below, the use of a summed value is discouraged. Chapter 5 presents an LCA data quality scoring system partly based on the DRI system.

The DRI method was developed because "in assessing data quality, one cannot really evaluate the quality of the data, but rather the quality of the data source(s) and the methodologies used in the generation of the data" (personal communication with H.P. Kollig). The DRI method can be used to assess the degree of confidence with which a literature value or data source can be used. A statistical procedure is not necessary for a DRI evaluation. Instead, a series of evaluation criteria are developed. Developing these criteria requires the use of experts who are familiar with the processes or properties under evaluation. Moreover, it is crucial to make certain that all important issues are evaluated.

The DRI measure is calculated by assigning weights to yes/no questions in four different categories: analytical information, experimental information, statistical information, and corroborative information. Examples of the questions and associated weights proposed by Kollig are as follows:

Data Reliability Indicator: Example
Analytical Information:
(4) Is the analytical method recognized as an acceptable method?
(5) Could you repeat the analytical part with the available information?
(2) Is the detection limit stated?
(3) Was high purity solvent used for extractions? (ignore if extractions not done)
Experimental Information:
(5) Could you repeat the experiment with the available information?
(3) Was a reference chemical of known constant tested?
(3) Was a control run?
(2) Were particulates absent?
Statistical Information
(3) Were replicate samples analyzed?
(3) Is the precision of the analytical technique reported?
(3) Is the precision of the sample analysis reported?
Corroborative Information
(5) Was the paper peer-reviewed?
(3) Do independent lab data confirm the results?
(2) Do estimated data confirm the results

For each question, an integer weight of 1 through 5, inclusive, is assigned (shown in parentheses next to each question). Components that are crucial to an analyst's degree of confidence in using the data source receive higher weights than those components that are less crucial. A source receives points only for questions receiving "yes" answers. If the answer to a question is "no," the source receives no points for that question.

In computing the final score, the four categories are considered separately. Within each category, the total number of points associated with the "yes" answers is summed. This number is then divided by the sum of the weights for each question in the category, regardless of the answer. This produces a ratio, or normalized score, between 0 (worst) and 1 (best). As indicated above, the scores are presented in the form (x, y, z, w).

APPENDIX D
DATA USABILITY

DATA USABILITY

A manual entitled *Guidance for Data Usability in Risk Assessment* (EPA, 1990) was developed to assist in determining minimum data quality requirements for environmental analytical data used in the clean-up of hazardous waste sites under the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA or Superfund). EPA developed six quantitative and qualitative criteria to determine the usability of the data for baseline human health risk assessments. These criteria consist of data sources, documentation, analytical methods and detection limits, DQIs, data review, and reports to the risk assessor. Unlike the NUSAP and DRI methods, which are used to analyze previously collected or generated data, EPA recommends that the data usability criteria be applied in the remedial investigation phase to guide the design of sampling plans and to select analytical methods for use in the data collection effort. The criteria should also be used to assess the usability of the analytical data collected during the remedial investigation, as well as data from other studies and sources.

The first data usability criterion, data sources, refers to the comparability of potential data sources. If different data sources will be combined for use in a quantitative risk assessment, comparable data sources should be used to avoid suspect results (EPA, 1990).

The second criterion, documentation, involves documenting deviations from the sampling and analysis plan and the standard operating procedures to denote limitations in the data. The third criterion stresses the need to choose appropriate analytical methods and detection limits. If the detection limits are chosen improperly, the samples may have to be reanalyzed at lower detection limits, thus wasting time and money on the reanalysis phase.

A group of DQIs is also considered in evaluating data usability. EPA suggests using the following DQIs in assessing risk assessment data: completeness, comparability, representativeness, precision, and accuracy. These DQIs play similar roles in the evaluation of data usability and LCA data quality.

In a baseline risk assessment, the use of preliminary or partially reviewed data can conserve time and resources by allowing modification of the sampling plan for the remedial investigation. Preliminary data can be used in a qualitative manner to identify compounds for toxicity studies, identify trends in concentrations and distributions of the analyses, plan for additional sampling, and request additional analyses. Partially reviewed data can improve the timeliness and overall efficiency of the risk assessment, as well as saving resources.

The final criterion concerns reports about the sampling and analytical procedures provided to the risk assessor. First, preliminary reports should be constructed to assist the assessor in identifying sampling or analytical problems so that corrective measures can be made during data collection. Secondly, the data reviewer should provide a narrative summary describing specific sampling or analytical problems, detection limits, and an interpretation of quality control data, as well as a detailed commentary addressing each of the issues in the narrative. EPA emphasizes that the narrative should be comprehensible to a nonchemist.

The process of determining data usability in risk assessments does not have a direct application to assessing LCA data quality. This is primarily due to the fact that the EPA-identified criteria are used to assess primary data gathered using statistical sampling procedures, while most of the data used in LCAs come from secondary sources.

APPENDIX E
BIBLIOGRAPHY

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